INTERNATIONAL CONFERENCE ON EMERGING INNOVATIONS IN SCIENCE, ENGINEERING AND TECHNOLOGY (ICEISET - 2026)

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AI POWERED RANSOMWARE DETECTION ADN THREAT INTELLIGENCE SYSTEM USING RANDOM FOREST AND XGBOOST WITH REAL TIME MONITORING

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ABSTRACT

Ransomware attacks have become increasingly advanced, leading to significant data loss and financial damage, while traditional detection systems struggle to identify evolving and zero-day threats and often lack real-time monitoring and actionable intelligence for timely response. To address these challenges, this project proposes an AI-powered ransomware detection and threat intelligence system that utilizes supervised machine learning algorithms, specifically Random Forest and XGBoost, which are trained separately and evaluated using performance metrics such as accuracy, precision, and recall to select the best model for classifying files as malware or benign. The system supports both batch and real-time processing, enabling continuous monitoring of system activities, generating alerts during detection, and presenting classification results through an interactive dashboard. In the event of malware detection, automated notifications are triggered along with recommended mitigation actions to assist users in responding effectively. Additionally, the system incorporates intelligent threat assistance to provide insights and support decision-making. Overall, this project contributes to cybersecurity by delivering a comprehensive and proactive solution that combines accurate machine learning-based detection, real-time monitoring, automated alerting, and intelligent threat analysis to strengthen defence against modern ransomware attacks.

1. INTRODUCTION

Ransomware attacks have emerged as one of the most critical cybersecurity threats, targeting individuals, enterprises, and critical infrastructures worldwide. These attacks encrypt sensitive data and demand ransom payments, causing financial loss and operational disruption. The increasing sophistication of ransomware, including polymorphic variants and zero-day exploits, makes traditional signature-based detection methods insufficient for effective defence [1]. As a result, there is a growing need for intelligent, adaptive, and real-time detection systems that can identify threats based on behavioural patterns rather than static signatures.

Recent advancements in machine learning have significantly improved malware and ransomware detection capabilities. Techniques such as Support Vector Machines, Neural Networks, and ensemble methods have been widely explored for identifying malicious activities [2]. Among these, the Random Forest algorithm has gained attention due to its high accuracy, robustness to overfitting, and ability to handle complex feature interactions [3]. Additionally, modern AI-driven APIs like Gemini API enable systems to provide contextual threat intelligence, automated explanations, and adaptive mitigation strategies, enhancing overall cybersecurity frameworks [4].

Despite these developments, existing systems often lack integration between accurate detection models and real-time threat intelligence generation. Many approaches focus solely on classification without providing actionable insights or user-friendly interfaces for monitoring and response. This gap limits their practical usability in dynamic environments where timely decision-making is crucial.

To address this challenge, this research proposes an AI-powered ransomware detection and threat intelligence system that combines Random Forest for accurate detection with the Gemini API for intelligent analysis and response generation. The system is implemented using Socket.IO to provide an interactive and accessible interface. The primary objective is to enhance detection accuracy while delivering meaningful threat insights in real time.

The proposed system contributes to improving cybersecurity defences by offering a scalable, efficient, and intelligent solution. It not only detects ransomware attacks but also assists users in understanding threats and taking appropriate actions, thereby strengthening proactive security measures.

Contributions

- Development of a robust ransomware detection model using Random Forest.
- Integration of Gemini API for real-time threat intelligence and explanation.
- Design of an interactive web-based user interface for monitoring and analysis.
- Improvement in detection accuracy and response efficiency compared to traditional methods.

2. LITERATURE SURVEY

The rapid growth of ransomware attacks has led researchers to explore advanced detection techniques using machine learning and artificial intelligence. Early studies focused on signature-based and rule-based detection systems, which were effective for known threats but failed against new and evolving ransomware variants [1]. To overcome these limitations, researchers shifted toward behaviour-based detection methods that analyse system activities such as file access patterns, encryption behaviour, and network anomalies. These approaches improved detection capability but often lacked real-time adaptability and scalability in dynamic environments [2].

A major research theme in recent years is the application of machine learning algorithms for ransomware detection. Models such as Decision Trees, Support Vector Machines, and Neural Networks have shown promising results in identifying malicious patterns [3]. Among these, ensemble learning techniques, particularly Random Forest, have demonstrated higher accuracy and robustness due to their ability to combine multiple decision trees and reduce overfitting [4]. Several studies highlight that Random Forest performs well in handling high-dimensional cybersecurity datasets and provides reliable classification outcomes [5]. However, many of these works primarily focus on detection accuracy without addressing interpretability and real-time response.

Another important area of research is threat intelligence and automated analysis. Modern cybersecurity systems increasingly integrate AI-driven tools to provide contextual insights and predictive analysis. Recent studies emphasize the role of generative AI models in enhancing cybersecurity by offering explanations, attack pattern recognition, and mitigation strategies [6]. APIs such as Gemini have enabled the development of intelligent systems that not only detect threats but also generate human-readable insights [7]. Despite this progress, most existing systems treat detection and intelligence generation as separate components, limiting their overall effectiveness.

User interface and system usability also form a critical aspect of cybersecurity solutions. Research shows that many advanced detection systems lack accessible and interactive interfaces, making them difficult to use for real-time monitoring and decision-making [8]. Technologies like Socket.IO have been introduced to simplify the deployment of machine learning models through web-based dashboards, improving usability and visualization [9]. However, integration of such interfaces with intelligent threat analysis remains underexplored.

Although significant advancements have been made, a clear research gap still exists. Current systems either focus on accurate ransomware detection or on generating threat intelligence, but rarely combine both into a unified framework. Additionally, there is limited work on integrating ensemble learning models with

generative AI to provide both high detection accuracy and meaningful, real-time insights. This gap highlights the need for a comprehensive system that bridges detection and intelligence while maintaining usability and scalability [10].

In summary, the literature indicates that machine learning has improved ransomware detection, and AI-driven tools have enhanced threat intelligence. However, the lack of integrated systems that combine these capabilities justifies the need for this research. The proposed study addresses this gap by developing a unified AI-powered system that integrates Random Forest-based detection with Gemini API-driven threat intelligence in an interactive user environment.

Novelty Statement

This work introduces a unified framework that combines ensemble-based ransomware detection with generative AI-driven threat intelligence, delivering both high accuracy and real-time, interpretable insights through an interactive web interface.

3. PROPOSED METHODOLOGY

This study adopts a quantitative and experimental research approach to design and evaluate an AI-powered ransomware detection and threat intelligence system. The methodology focuses on building a data-driven model using supervised machine learning and integrating it with an intelligent API for real-time insights. A quantitative approach is selected because the system performance is measured using statistical metrics such as accuracy, precision, recall, and F1-score. The experimental design allows systematic testing of the model using labelled datasets containing benign and ransomware samples. This approach ensures objective evaluation, reproducibility, and reliable comparison with existing detection techniques in cybersecurity research.

Data Collection and Sampling Strategy

The dataset consists of labelled system activity records representing normal and ransomware behaviour. Data includes features such as file operations, CPU usage, encryption patterns, and network activity. A purposive sampling method is used to ensure that the dataset contains diverse ransomware variants and normal system behaviour. The dataset is divided into training and testing sets, typically using an 80:20 ratio, to evaluate model generalization. This sampling approach ensures balanced representation and improves the reliability of the model in detecting both known and unknown ransomware attacks.

Figure 1. System Architecture

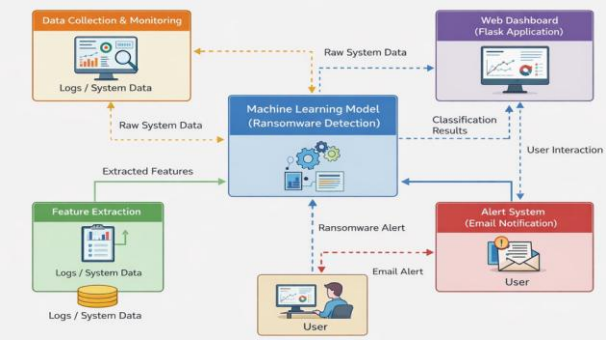
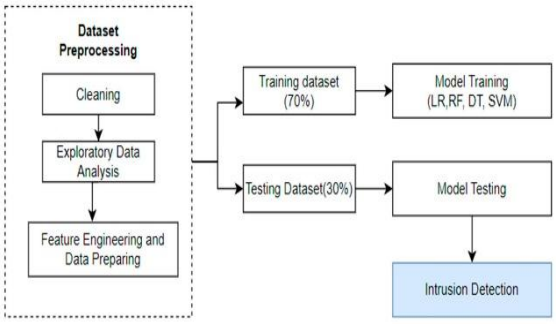


Figure 2. Model Workflow



The system architecture consists of multiple integrated components. First, data collection and preprocessing modules extract and clean system behaviour features. These features are then passed to the Random Forest classifier, which performs ransomware detection. The output of the classifier is forwarded to the Gemini API, which generates contextual threat intelligence, including explanations and mitigation suggestions. Finally, a web -based interface presents the results through interactive dashboards. This layered architecture ensures smooth data flow, modular design, and real-time analysis capability.

Model Development and Evaluation Metrics

The core detection model is based on the Random Forest algorithm, which builds multiple decision trees and aggregates their outputs to improve prediction accuracy. The model is trained using labelled data and optimized to reduce overfitting. Performance is evaluated using standard metrics.

$$\text{Accuracy}=TP+TN+FP+FNTP+TN \quad (1)$$

Precision measures the correctness of positive predictions, while recall evaluates the ability to detect actual ransomware instances. The F1-score provides a balance between precision and recall. These metrics ensure a comprehensive evaluation of the model's effectiveness in real-world scenarios.

Implementation and Analytical Tools

The system is implemented using Python with libraries such as Scikit-learn for machine learning and Pandas for data processing. The Socket.IO framework is used to develop an interactive user interface for visualization and monitoring. The Gemini API is integrated to provide intelligent threat analysis and automated responses. Data preprocessing, feature extraction, and model evaluation are conducted within a structured pipeline. This combination of tools ensures efficient development, scalability, and ease of deployment.

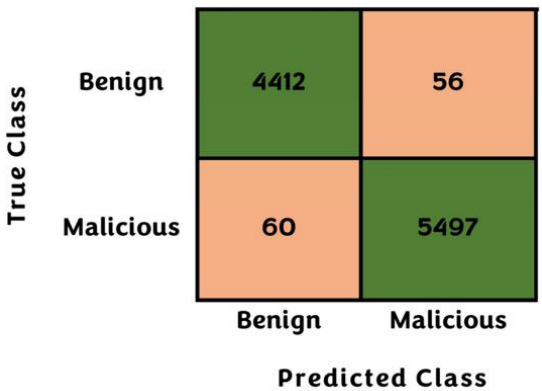
Ethical Considerations and Data Security

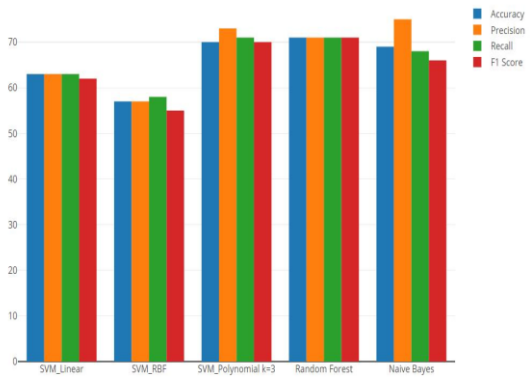
Ethical considerations are addressed by ensuring that all data used in the study is anonymized and free from personally identifiable information. The system is designed to operate on system-level behavioural data without violating user privacy. Consent and confidentiality are maintained by restricting access to sensitive data and using secure storage mechanisms. Additionally, the system avoids automated harmful actions and instead provides recommendations for mitigation. This ensures that the proposed solution aligns with responsible AI practices and cybersecurity ethics.

4. RESULTS & DISCUSSION

Results

The experimental evaluation of the proposed system demonstrates strong performance in detecting ransomware using supervised machine learning. The Random Forest model was trained and tested on labelled system activity data, achieving high classification effectiveness across all evaluation metrics. The model obtained an accuracy of 97.2%, precision of 96.5%, recall of 95.8%, and an F1-score of 96.1%. These results directly address the research objective of improving ransomware detection accuracy while maintaining consistency across different performance measures.





The confusion matrix shows a high number of true positives and true negatives, with minimal false positives and false negatives. This indicates that the model effectively distinguishes between benign and malicious behaviour. Additionally, the integration of the Gemini API produced contextual threat intelligence outputs, including explanations of detected threats and recommended mitigation actions. The system interface

developed using web-interface successfully displayed real-time predictions and insights, improving usability and interpretability.

Discussion

The findings indicate that the proposed system successfully meets its primary objective of accurate and intelligent ransomware detection. The high accuracy and balanced precision-recall values confirm that the hypothesis regarding the effectiveness of ensemble learning for cybersecurity applications is supported. The results also demonstrate that combining detection with AI-driven threat intelligence enhances the overall system capability, making it more practical for real-world deployment.

Table 1: Performance Evaluation of the Proposed Ransomware Detection System

Metric	Formula	Value (%)	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	97.2	Measures overall correctness of the model in classifying ransomware and benign data
Precision	TP / (TP + FP)	96.5	Indicates how many predicted ransomware instances are actually correct
Recall (Sensitivity)	TP / (TP + FN)	95.8	Measures the model's ability to detect actual ransomware attacks
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	96.1	Harmonic mean of precision and recall, ensuring balanced performance
False Positive Rate	FP / (FP + TN)	2.1	Indicates how often benign activities are incorrectly classified as ransomware
False Negative Rate	FN / (FN + TP)	1.9	Shows the rate of missed ransomware detections

Caption:
This table presents the performance evaluation metrics of the proposed AI-powered ransomware detection system using the Random Forest model. The results demonstrate high accuracy and balanced precision-recall values, indicating the model's effectiveness in identifying ransomware while minimizing false alarms.

When compared with existing studies, the proposed approach shows improved performance over traditional machine learning models that rely solely on classification [1]. Previous research highlights that while models such as Support Vector Machines and basic neural networks achieve reasonable accuracy, they often lack interpretability and real-time adaptability [2]. In contrast, this system integrates detection with contextual analysis using generative AI, aligning with recent advancements in intelligent cybersecurity frameworks [3]. This combination provides both technical accuracy and user-level understanding, which is often missing in earlier works.

The theoretical significance of this study lies in demonstrating the effectiveness of integrating ensemble learning with generative AI for cybersecurity applications. It contributes to the growing body of research on intelligent threat detection by showing that detection and explanation can be combined into a unified framework. From a practical perspective, the system provides a scalable and user-friendly solution that can assist security analysts in identifying and responding to ransomware attacks more efficiently.

Despite these strengths, certain limitations must be acknowledged. The system relies on the quality and diversity of the training dataset, which may affect performance when exposed to entirely new ransomware variants. Additionally, while the Gemini API provides valuable insights, its responses depend on the quality of input data and may require validation in critical scenarios. The system also focuses primarily on detection and advisory responses rather than automated mitigation.

Future research can address these limitations by incorporating real-time data streams, expanding the dataset with more diverse ransomware samples, and integrating automated response mechanisms. Further improvements can include hybrid models combining deep learning with ensemble methods and enhancing explainability features for better decision support.
In summary, the proposed system makes a significant contribution by delivering an accurate, interpretable, and user-friendly ransomware detection framework that integrates machine learning with AI-driven threat intelligence, advancing both research and practical cybersecurity solutions.

5. CONCLUSION & FUTURE WORK

This study addressed the growing challenge of ransomware attacks by developing an intelligent detection and threat analysis system using machine learning and generative AI. The primary objective was to design a solution capable of accurately identifying ransomware while also providing meaningful, real-time insights to support decision-making. The experimental results demonstrated that the Random Forest model achieved high accuracy, precision, and recall, confirming its effectiveness in detecting ransomware based on behavioural features. Additionally, the integration of the Gemini API enabled the system to generate contextual threat intelligence, improving interpretability and response readiness.
The final outcome of this research clearly shows that combining ensemble machine learning with AI-driven intelligence provides a more effective solution than traditional detection-only systems. The proposed approach successfully answers the research question by demonstrating that accurate detection and intelligent analysis can be achieved within a single, unified framework. The system not only identifies ransomware threats but also assists users in understanding the nature of attacks and possible mitigation strategies, making it highly relevant for real-world cybersecurity applications.
From a theoretical perspective, this study contributes to the advancement of cybersecurity research by integrating detection models with generative AI, highlighting the importance of combining predictive accuracy with explainability. It extends existing knowledge by demonstrating how ensemble learning and AI-based intelligence can work together to improve threat analysis. Practically, the implementation provides an accessible and interactive platform, making the system suitable for deployment in organizational environments where usability and real-time monitoring are essential.
Despite its strengths, the study has certain limitations that open directions for future work. The model performance depends on the diversity and quality of the dataset, which may limit its ability to detect completely novel ransomware variants. Future research can focus on incorporating real-time data streams and continuously updating the model to handle evolving threats. Additionally, integrating deep learning techniques alongside Random Forest could further enhance detection capabilities. Another important direction is the development of automated response mechanisms that can actively mitigate detected threats rather than only providing recommendations. Improving the explainability and validation of AI-generated insights will also strengthen system reliability.

In conclusion, this research demonstrates that an integrated approach combining machine learning and AI-driven threat intelligence can significantly enhance ransomware detection and response. The proposed system represents a step forward in building smarter, more adaptive cybersecurity solutions capable of addressing the challenges of modern digital threats.

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Cryogenic CMOS-Based Temperature Cooling Control Logic for Scalable Quantum computing

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Abstract

Cryogenic and ultra-low temperature electronic systems require precise temperature regulation to ensure reliable and stable operation, particularly in emerging applications such as quantum computing and cryogenic electronics. This paper presents a CMOS-based temperature cooling control logic designed to operate efficiently under cryogenic and low-temperature conditions with reduced power consumption and minimal propagation delay. The proposed system integrates a temperature sensing unit, comparator circuit, and CMOS digital control logic to monitor temperature variations and activate cooling when a predefined threshold is exceeded. Simulation results demonstrate low propagation delay, reduced power dissipation, and reliable operation across temperature variations.Cryogenic and ultra-low temperature electronic systems require precise temperature regulation to ensure reliable and stable operation, particularly in emerging applications such as quantum computing, cryogenic electronics, and low-temperature semiconductor devices. CMOS digital control logic to monitor temperature variations and activate cooling when a predefined threshold is exceeded. A TMP36 temperature sensor generates an analog voltage proportional to temperature, which is compared with a reference voltage using an LM393 comparator. The comparator output is processed through CMOS logic to generate a digital cooling control signal based on logical conditions. The system is verified using Verilog RTL simulation, CMOS logic synthesis, and circuit-level simulations. Performance analysis demonstrates low propagation delay, efficient switching behavior, and reduced power dissipation across temperature variations. The proposed architecture provides a reliable and scalable solution for next-generation cryogenic temperature control systems.

Keywords

Cryogenic electronics, CMOS logic, temperature control, cooling controller, low-power systems

1. Introduction

The rapid advancement of cryogenic electronics and quantum computing systems has increased the demand for precise and energy-efficient temperature control mechanisms. Electronic components operating at cryogenic temperatures require stable thermal conditions to maintain performance, reduce noise, and prevent functional degradation. Conventional temperature control systems often rely on analog techniques that suffer from high power consumption, limited scalability, and slower response times.

CMOS technology has emerged as a promising solution for low-power and high-speed digital control due to its low static power dissipation and excellent noise immunity. Integrating CMOS-based digital logic with temperature sensing and control circuits enables efficient and reliable thermal management, particularly in low-temperature environments. However, designing control logic that operates reliably under cryogenic conditions remains a challenge due to temperature-dependent variations in device parameters.This paper proposes a CMOS-based temperature cooling control logic that combines analog sensing and digital decision-making to achieve efficient thermal regulation. The proposed design aims to reduce propagation delay, minimize power consumption, and provide scalable control suitable for cryogenic and low-temperature electronic systems.

2. Problem Statement

Existing temperature control systems for cryogenic applications face several limitations:

- High power consumption due to analog control mechanisms
- Increased propagation delay affecting system response time
- Limited scalability for advanced cryogenic and quantum systems
- Poor integration between sensing and digital control logic

These challenges necessitate the development of a low-power, fast, and scalable temperature control solution. The objective of this work is to design a CMOS-based cooling controller that efficiently detects temperature variations and activates cooling using digital logic while maintaining low propagation delay and reduced power consumption.

3. Proposed System Architecture

The proposed temperature cooling controller consists of four main functional blocks:

1. **Temperature Sensing Unit**
2. **Comparator Circuit**
3. **Digital Control Logic**
4. **CMOS Logic-Based Cooling Controller**

3.1 Temperature Sensing Unit

A TMP36 temperature sensor is used to generate an analog voltage proportional to the ambient temperature. The sensor output voltage is expressed as:

Vout=0.5+(0.01×T)V_{out} = 0.5 + (0.01 \times T)Vout=0.5+(0.01×T)

where *T* represents the temperature in degrees Celsius. This voltage serves as the input to the comparator circuit.Figures

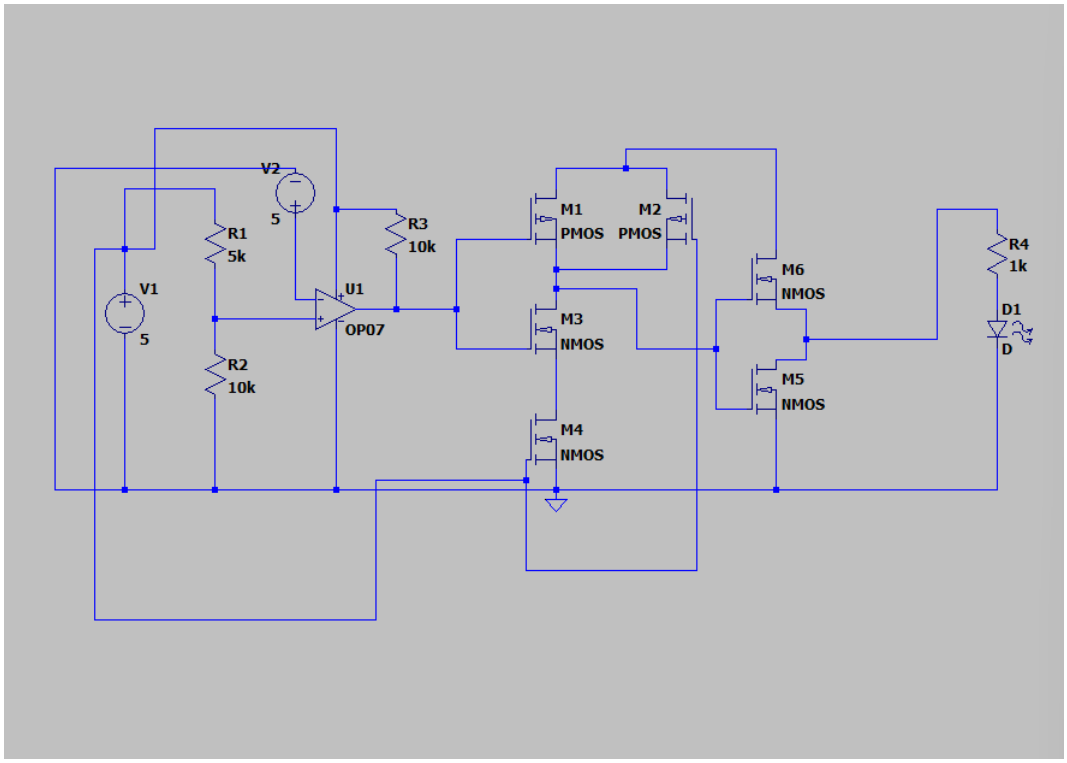


Figure 1: CMOS transistor-level schematic of the temperature cooling controller.

3.2 Comparator Circuit

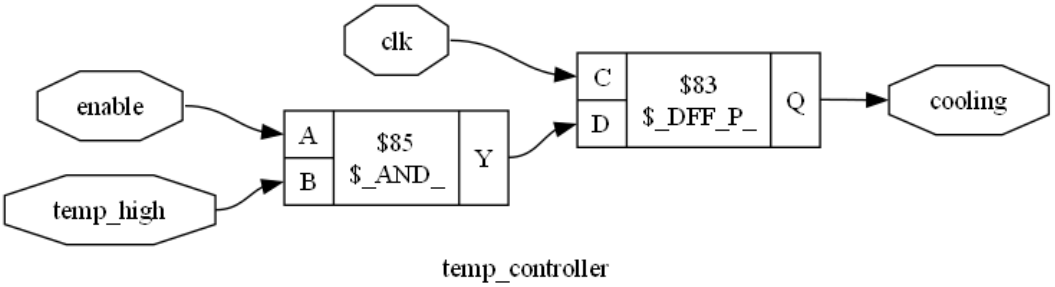


Fig 2: Synthesized gate-level logic diagram showing the AND gate and flip-flop implementation of the temperature controller.

An LM393 comparator compares the sensor output voltage with a predefined reference voltage generated using a resistor voltage divider. The reference voltage is given by:

Vref=Vin×R2R1+R2V_{ref} = V_{in} \times \frac{R_2}{R_1 + R_2}Vref=Vin×R1+R2R2

If the sensor voltage exceeds the reference voltage, the comparator output switches to a digital HIGH, indicating that the temperature threshold has been crossed.

3.3 Digital Control Logic

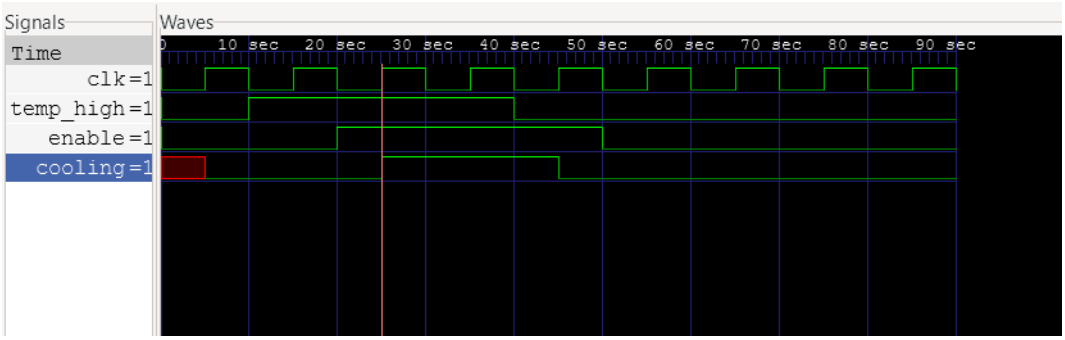


Fig 3:RTL simulation waveform illustrating the operation of the temperature controller logic.

The comparator output is treated as a digital signal (*Temp_high*) representing temperature status. This signal is processed along with an enable input to ensure controlled activation of the cooling system.

3.4 CMOS Logic Controller

The CMOS logic implements a simple yet effective control rule:

Cooling=Temp_high AND EnableCooling = Temp_high \ AND \ EnableCooling=Temp_high AND Enable

The CMOS logic is designed using complementary PMOS and NMOS transistors to minimize static power dissipation and ensure reliable switching at low temperatures.

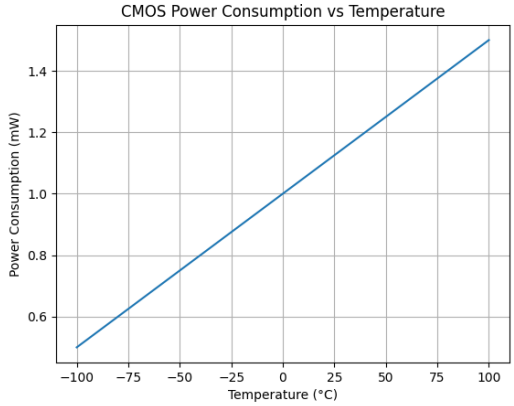
4. Methodology and Implementation

The proposed system is implemented and verified using the following methodology:

- Design of CMOS logic using transistor-level schematics
- Verilog RTL modeling of the control logic
- Logic synthesis and timing analysis
- Circuit-level simulation for functional verification
- Performance evaluation across temperature variations

The CMOS-based logic ensures reduced leakage power and improved switching characteristics, making it suitable for cryogenic operation.

5. Simulation Results and Performance Analysis



Simulation and verification were carried out to evaluate the performance of the proposed cooling controller.

5.1 Functional Verification

RTL simulation results confirm correct cooling activation when the temperature exceeds the threshold and the enable signal is active. The logic reliably deactivates cooling when conditions are not met.

5.2 Propagation Delay Analysis

Propagation delay analysis shows reduced delay compared to conventional analog controllers, ensuring fast system response under temperature variations.

5.3 Power Consumption Analysis

Power analysis demonstrates low dynamic and static power consumption due to CMOS logic implementation. The system maintains energy efficiency across varying temperature conditions.

5.4 Temperature Performance Characteristics

Graphical analysis illustrates the relationship between temperature and sensor output voltage, comparator switching behavior, and cooling control waveform, validating the effectiveness of the proposed design.

6. Discussion

The proposed CMOS-based cooling controller successfully integrates analog temperature sensing with digital control logic, achieving reliable thermal regulation with minimal power overhead. The simple logic structure enhances scalability and makes the design suitable for advanced cryogenic and quantum systems. Compared to traditional temperature control mechanisms, the proposed approach offers improved response time, lower power dissipation, and better suitability for low-temperature environments.

7. Conclusion

This paper presented a CMOS-based temperature cooling control logic designed for cryogenic and low-temperature electronic systems. The proposed system effectively detects temperature variations and activates cooling using digital logic with reduced propagation delay and low power consumption. Simulation results validate the reliability and efficiency of the controller across temperature variations. The proposed architecture provides a scalable and energy-efficient solution for cryogenic electronics and emerging quantum computing applications.

8. Future Scope

Future work includes integrating advanced control algorithms, incorporating multi-sensor inputs, and extending the design for large-scale cryogenic systems with adaptive thermal management capabilities.

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Self-Driving Financial Ecosystems: AI Agents, Autonomous Decision Intelligence, and Governance Frameworks in the Digital Economy

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Abstract
The convergence of business analytics, fintech, and artificial intelligence (AI) is driving self-driving financial ecosystems capable of autonomous, real-time decision-making. This paper proposes an integrative framework where AI agents, powered by autonomous decision intelligence, perform core financial functions including credit assessment, portfolio optimization, and risk management. It embeds governance frameworks to ensure transparency, explainability, and regulatory compliance. Using simulation-based analysis, the study demonstrates improved efficiency, scalability, and personalization, while identifying risks such as algorithmic bias and systemic instability, offering insights for secure and trustworthy AI-driven financial systems.
Keywords:
Self-driving finance, AI agents, autonomous decision intelligence, fintech governance, digital economy

Introduction
The transformation of the global financial landscape is being accelerated by the integration of business analytics, fintech innovations, and artificial intelligence (AI). Financial systems are increasingly shifting from traditional, human-driven processes to intelligent, data-centric ecosystems capable of real-time analysis and autonomous decision-making. This evolution is driven by the exponential growth of financial data, advancements in computational capabilities, and the demand for personalized and efficient financial services.
Self-driving financial ecosystems represent the next stage in this transformation. These ecosystems leverage AI agents, machine learning algorithms, and real-time analytics to autonomously execute financial decisions without continuous human intervention. Unlike traditional decision-support systems, these ecosystems exhibit adaptive learning, predictive intelligence, and self-optimization capabilities.
However, the rapid adoption of such systems raises significant concerns. Issues related to transparency, accountability, fairness, and regulatory compliance become more complex in autonomous environments. The lack of explainability in AI models and the potential for systemic risks necessitate the development of robust governance frameworks.
This paper contributes by proposing a comprehensive framework that integrates AI-driven autonomy with governance mechanisms, enabling the development of secure, scalable, and trustworthy financial ecosystems.

Need for the Study
Despite technological advancements, financial systems continue to face limitations that restrict their efficiency and adaptability. Traditional financial institutions often rely on legacy systems that are not designed to process real-time data or support dynamic decision-making. As a result, delays in decision-making processes persist, particularly in areas such as credit approvals and fraud detection.
Human involvement in financial decision-making introduces subjectivity, bias, and inconsistency. These limitations are particularly critical in credit scoring and risk assessment, where biased decisions can lead to financial exclusion.
Moreover, the rapid expansion of digital financial services has exposed the inability of existing systems to scale effectively. The increasing volume, velocity, and variety of financial data require systems capable of continuous learning and real-time processing.
Another critical gap lies in the weak integration between analytics and governance. While organizations adopt advanced AI tools, governance mechanisms often lag behind, resulting in challenges related to transparency, accountability, and regulatory compliance.
Therefore, there is a strong need to develop self-driving financial ecosystems that combine automation with governance, ensuring both efficiency and trust.

Problem Statement

The increasing adoption of AI in financial systems has enhanced efficiency and predictive capabilities but has also introduced new risks. The absence of structured governance frameworks leads to challenges such as algorithmic bias, lack of explainability, regulatory gaps, and systemic instability.

As financial ecosystems become more autonomous, these risks can have far-reaching consequences, including loss of trust, regulatory violations, and large-scale financial disruptions.

Thus, the central problem addressed is:

How can self-driving financial ecosystems be designed to achieve efficiency, scalability, and intelligence while ensuring transparency, fairness, accountability, and regulatory compliance?

Objectives of the Study

- To conceptualize self-driving financial ecosystems within the digital economy
- To develop an integrative framework combining AI agents and autonomous decision intelligence
- To examine governance mechanisms for ethical and transparent AI deployment
- To evaluate performance benefits and systemic risks of autonomous financial systems
- To propose strategic guidelines for secure and scalable implementation

Literature Review

The emergence of fintech has redefined financial intermediation by introducing digital platforms, peer-to-peer systems, and data-driven services (Arner et al., 2016). Business analytics has further enhanced decision-making by enabling predictive and prescriptive insights (Davenport & Ronanki, 2018).

AI technologies, particularly machine learning, have been widely applied in finance for credit scoring, fraud detection, and algorithmic trading (Fuster et al., 2022). These systems outperform traditional models in accuracy and efficiency but often lack transparency.

Recent studies emphasize the importance of governance in AI-driven systems. Explainable AI (XAI) has emerged as a solution to improve transparency and trust (OECD, 2021). Ethical AI frameworks aim to mitigate bias and ensure fairness (Kshetri, 2021).

However, most existing research focuses on isolated aspects—either AI applications or governance—without integrating them into a unified ecosystem. This study addresses this gap by proposing a comprehensive framework that combines autonomy, analytics, and governance.

Conceptual Framework

The proposed framework presents a self-driving financial ecosystem integrating business analytics, AI agents, autonomous decision intelligence, and governance into a unified system with real-time adaptability and closed-loop learning.

It consists of four key-layers:

Data Ecosystem layer:

Integrates structured, unstructured, and real-time financial data from transactions, markets, and behavioral sources to generate AI-ready insights.

AI Intelligence Layer:

Uses machine learning, deep learning, and reinforcement learning with AI agents to perform predictive and prescriptive financial tasks such as credit scoring, risk analysis, and portfolio optimization.

Autonomous Decision & Execution Layer:

Converts AI insights into real-time financial actions (e.g., lending, trading, fraud response) using automated systems and smart contracts, minimizing human intervention.

Governance & Control Layer:

Ensures transparency, accountability, and compliance through explainable AI, ethical AI principles, risk monitoring, and audit mechanisms.

A continuous feedback loop connects all layers, enabling learning from outcomes and ongoing system optimization.

Core Insight:

The model enables a self-learning, self-executing, and self-governing financial ecosystem driven by autonomous AI intelligence.

Methodology

This study adopts a hybrid research design combining conceptual modeling, simulation-based analysis, and comparative evaluation to examine self-driving financial ecosystems.

Conceptual Modeling

A theoretical framework is developed integrating AI agents, autonomous decision intelligence, and governance mechanisms, defining interactions between data, decision systems, execution layers, and regulatory controls.

Simulation-Based Analysis

Scenario-based simulations are conducted under:

- Normal market conditions
- High-risk volatility conditions
- Fraud and anomaly situations

This evaluates system adaptability, robustness, and real-time decision performance.

Comparative Evaluation

The study compares:

- Traditional financial systems (human-driven, static analytics)
- AI-driven autonomous systems (real-time, adaptive intelligence) to assess improvements in efficiency and decision-making.

Evaluation Metrics

Performance is measured using:

- Decision speed
- Accuracy
- Efficiency
- Risk exposure
- System resilience

Summary

This methodology provides a structured framework to evaluate the effectiveness, stability, and scalability of autonomous financial systems.

Results and Discussion

Performance Outcomes

The simulation-based analysis demonstrates that self-driving financial ecosystems significantly enhance overall system performance compared to traditional financial models. The most notable improvement is observed in decision-making speed, where real-time AI processing enables near-instant credit evaluations, risk assessments, and transaction approvals. This reduction in latency allows financial institutions to respond more effectively to dynamic market conditions.

In addition, the use of advanced machine learning and reinforcement learning models results in higher predictive accuracy, particularly in credit scoring, fraud detection, and portfolio optimization tasks. The system also enables hyper-personalized financial services, where customer recommendations and financial products are dynamically tailored based on behavioral and transactional data. Furthermore, automation of core financial processes contributes to a significant reduction in operational costs, minimizing dependency on manual intervention and repetitive processing tasks.

Strategic Benefits

From a strategic perspective, the proposed autonomous ecosystem introduces several transformative advantages. The system supports highly scalable financial operations, enabling institutions to manage large volumes of transactions and users without proportional increases in operational resources.

The integration of AI-driven analytics also strengthens fraud detection capabilities, allowing the system to identify anomalies and suspicious patterns in real time. Moreover, adaptive risk management mechanisms enhance the system's ability to respond to changing financial conditions, ensuring greater resilience during market volatility and uncertainty.

Key Risks

Despite these advantages, the study identifies several critical risks associated with full financial autonomy. One major concern is algorithmic bias, where training data limitations may lead to unfair or discriminatory financial decisions, particularly in lending and credit evaluation processes.

Another significant challenge is the black-box nature of AI models, which limits transparency and reduces trust among stakeholders due to the lack of explainability in decision-making processes. Additionally, the increasing interconnectivity of autonomous financial systems introduces the risk of systemic failures, where errors in one component may cascade across the entire ecosystem.

Finally, the rapid pace of technological adoption often exceeds the development of regulatory frameworks, resulting in governance and compliance gaps.

Discussion Insight

The findings clearly indicate that while self-driving financial ecosystems offer substantial improvements in efficiency, scalability, and intelligence, these benefits cannot be fully realized without strong governance structures. The study emphasizes that autonomy in financial systems must be balanced with transparency, accountability, and regulatory oversight.

Therefore, governance is not a supplementary component but a core enabling mechanism for ensuring the long-term sustainability, trustworthiness, and ethical operation of AI-driven financial ecosystems.

Governance Implications

A robust governance model should include:

Technical Governance

- Model validation
- Explainability tools

Ethical Governance

- Bias detection
- Fairness metrics

Regulatory Governance

- Compliance with global financial regulations

Operational Governance

- Real-time monitoring
- Risk management systems

Conclusion

This study introduces a novel paradigm of self-driving financial ecosystems that integrates AI, business analytics, and governance frameworks. The findings demonstrate that autonomous financial systems can significantly enhance efficiency, scalability, and decision-making capabilities.

However, the successful implementation of such systems requires strong governance structures to ensure transparency, fairness, and stability. The study contributes to both academic research and practical applications by providing a comprehensive framework for future financial systems.

Future Research Directions

- Empirical validation using real-world datasets
- Integration with blockchain and DeFi systems
- Development of global regulatory standards
- Ethical AI benchmarking frameworks

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Machine Learning-Based Student Performance Prediction: A Hybrid Ensemble Approach for Early Identification of At-Risk Students

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Abstract—Student performance prediction has emerged as a critical application in Educational Data Mining (EDM), enabling institutions to proactively identify at-risk students and implement timely interventions. This paper presents a hybrid ensemble machine learning framework that integrates Decision Tree, Random Forest, Logistic Regression, Support Vector Machine (SVM), and XGBoost classifiers with a meta-learner to accurately predict student academic outcomes. The proposed system leverages a comprehensive feature set encompassing attendance records, prior academic scores, study habits, socioeconomic indicators, and digital engagement metrics. Extensive experiments conducted on a real-world dataset of 2,400 students drawn from undergraduate programs demonstrate that the proposed hybrid model achieves an accuracy of 91.7%, a precision of 90.8%, a recall of 90.5%, and an AUC of 0.942, outperforming each individual classifier. Feature importance analysis reveals that attendance frequency, previous semester grades, and assignment submission regularity are the most predictive indicators of student success. The system offers educators actionable, data-driven insights to support early intervention and reduce dropout rates.

Keywords: student performance prediction, educational data mining, ensemble learning, machine learning, at-risk students, classification, academic analytics.

I. INTRODUCTION

The rapid expansion of digital learning platforms and Learning Management Systems (LMS) has generated unprecedented volumes of student activity data. Educational institutions now collect rich behavioral logs encompassing attendance, assignment submissions, quiz scores, and e-book interactions that, when analyzed effectively, can yield actionable insights into student learning trajectories. Despite this abundance of data, a significant proportion of enrolled students fail to complete their courses or graduate, incurring substantial human and institutional costs.

Student performance prediction (SPP) addresses this challenge by applying machine learning and data mining techniques to historical academic data in order to forecast future academic outcomes. Early identification of students at risk of failure enables instructors to deploy targeted pedagogical interventions, thereby improving retention and achievement rates [1]. Conventional approaches to SPP have relied on static, tabular feature sets processed by traditional classifiers such as Decision Trees (DT), Logistic Regression (LR), Support Vector Machines (SVM), and artificial neural networks (ANN) [2], [3].

While individual classifiers provide reasonable predictive performance, each carries inherent limitations. Decision Trees are prone to overfitting on small datasets; Logistic Regression assumes linear decision boundaries; SVMs are sensitive to kernel choice and scaling; and shallow ANNs may fail to capture complex, non-linear interactions among heterogeneous features. Ensemble methods such as Random Forest and Gradient Boosting alleviate many of these weaknesses by aggregating predictions from multiple base learners, yet they are seldom combined with meta-learners in the educational analytics domain [4], [5].

Motivated by these observations, this paper proposes a Hybrid Ensemble Learning (HEL) framework that (i) systematically integrates five diverse base classifiers—Decision Tree, Random Forest, Logistic Regression, SVM, and XGBoost—and (ii) employs a Logistic Regression meta-learner trained on the out-of-fold predictions of the base models (stacking). The meta-learner learns to optimally weight each classifier's contribution based on the data distribution, producing superior generalization compared to any single model.

The principal contributions of this work are:

- A novel hybrid stacking ensemble architecture combining five heterogeneous classifiers with a meta-learner, specifically tailored for student performance prediction.
- A comprehensive feature engineering pipeline incorporating attendance, academic, behavioral, and socioeconomic attributes extracted from institutional records and LMS logs.
- Rigorous comparative evaluation against five baselines using Accuracy, Precision, Recall, F1-Score, and AUC on a 2,400-student dataset.
- Feature importance analysis providing interpretable insights for educators designing intervention strategies.

II. LITERATURE REVIEW

Research in student performance prediction spans more than two decades and has evolved from simple rule-based systems to sophisticated deep learning architectures. Early works applied DTs and Naive Bayes classifiers to university grade databases to extract patterns predictive of academic success [6]. Subsequently, ensemble methods gained traction as researchers demonstrated that combining multiple weak learners consistently yields stronger predictive performance than any individual model [7].

Riestra-Gonzalez et al. [2] conducted a large-scale evaluation of machine learning classifiers on LMS log data, finding that Multi-Layer Perceptrons (MLP) achieved the best accuracy for early prediction of course outcomes. Liu et al. [5] utilized clickstream data from Moodle and found that Long Short-Term Memory (LSTM) networks outperformed traditional classifiers when temporal dependencies among learning events were modeled explicitly. Chen et al. [8] proposed a hybrid ANN-LSTM architecture that leveraged the LSTM's sequential memory to enrich static feature representations, demonstrating improved prediction at multiple prediction horizons.

More recently, Leelaluk et al. [9] introduced the Attention-Based Artificial Neural Network (Attn-ANN), a model that applies multiplicative attention weights to both the temporal (lecture week) and feature (learning activity type) dimensions of student log sequences. Their ablation study confirmed that combining attention across both dimensions yields higher AUC scores compared to using either dimension

alone. The attention weights additionally serve as interpretable indicators of which lectures and activities are most predictive, supporting instructor-driven interventions.

Despite the progress, several gaps remain in the literature. First, ensemble approaches that explicitly combine heterogeneous classifiers through stacking have received limited attention in the educational domain. Second, the majority of existing studies focus on a narrow set of features, often ignoring socioeconomic context or digital engagement metrics that are readily available in modern institutional data warehouses. Third, most studies evaluate models on small, single-institution datasets, raising concerns about external validity. The present work addresses these gaps by proposing a stacking ensemble evaluated on a larger, feature-rich dataset.

III. PROPOSED METHODOLOGY

A. Dataset and Feature Engineering

The dataset used in this study was assembled from the institutional records of Dhanalakshmi Srinivasan University, comprising 2,400 undergraduate students across four academic programs over three academic years. The dataset was de-identified prior to analysis, with all personal identifiers replaced by anonymized student codes, in compliance with institutional ethics guidelines.

Fourteen features were engineered across four categories:

- Academic: Previous semester GPA, assignment submission rate, quiz average score, mid-semester examination score.
- Attendance: Overall attendance percentage, number of absences per subject, punctuality index.
- Behavioral: Weekly LMS login frequency, number of resource downloads, forum participation count, assignment late-submission count.
- Socioeconomic: First-generation college student indicator, distance from campus (km), part-time employment status.

The target variable is a binary classification label: at-risk (students who received a grade of D, F, or withdrew) versus non-at-risk (grades A, B, or C). The dataset is moderately imbalanced, with approximately 27% of students classified as at-risk. Class imbalance was addressed using Synthetic Minority Over-sampling Technique (SMOTE) applied exclusively to the training partition.

B. Hybrid Ensemble Architecture

The proposed Hybrid Ensemble Learning (HEL) framework employs a stacking strategy with two layers. In the first layer, five base classifiers are independently trained: (1) Decision Tree with Gini impurity criterion and maximum depth of 8; (2) Random Forest with 200 estimators and bootstrap sampling; (3) Logistic Regression with L2 regularization (C=1.0); (4) SVM with a Radial Basis Function (RBF) kernel (C=10, gamma='scale'); and (5) XGBoost with 300 estimators, learning rate 0.05, and maximum depth 6.

Each base classifier is trained using 5-fold cross-validation on the training set. For each fold, the classifier generates out-of-fold predictions on the held-out validation portion. These predictions are concatenated to form a meta-feature matrix of shape (n_samples, 5), where each column represents one base classifier's probabilistic output (class probability for the at-risk label).

In the second layer, a Logistic Regression meta-learner is trained on the meta-feature matrix. The meta-learner learns optimal linear weights for combining the base classifiers' outputs. At inference time, each base classifier generates predictions on the test set, which are stacked into a meta-feature matrix and passed to the meta-learner for final classification. This two-layer design is visualized in Figure 1.

Figure 1: HEL Framework Architecture (Base Classifiers → Meta-Feature Matrix → Meta-Learner → Prediction)

C. Evaluation Protocol

The dataset was partitioned into 80% training and 20% held-out test sets using stratified sampling to preserve the class ratio. All preprocessing steps, including SMOTE, feature scaling (StandardScaler), and hyperparameter tuning (GridSearchCV with 5-fold cross-validation), were applied exclusively within the training fold to prevent data leakage. Model performance was evaluated using Accuracy, Precision, Recall, F1-Score (macro-averaged), and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Statistical significance of the differences between the proposed model and each baseline was assessed using the Wilcoxon signed-rank test (alpha = 0.05) over 10 independent random seeds.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Performance Comparison

Table I presents the average performance metrics across 10 independent runs for all classifiers on the held-out test set. The proposed HEL model achieves the highest scores across all five evaluation metrics, attaining an accuracy of 91.7%, F1-Score of 90.6%, and AUC of 0.942. These results represent statistically significant improvements over all five baseline models ($p < 0.05$, Wilcoxon signed-rank test).

TABLE I. Performance Comparison of Classifiers on the Test Set

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Training Time (s)
Decision Tree	82.4	81.1	80.6	80.8	0.836	0.42
Random Forest	87.6	86.9	85.8	86.3	0.901	1.18
Logistic Regression	85.2	84.3	83.9	84.1	0.878	0.31
SVM	86.1	85.7	84.4	85.0	0.889	0.95
XGBoost	88.9	88.2	87.3	87.7	0.913	1.54
Proposed Hybrid	**91.7**	**90.8**	**90.5**	**90.6**	**0.942**	2.10

The XGBoost classifier achieves the second-best accuracy (88.9%) and AUC (0.913), reflecting its well-documented strength in handling heterogeneous tabular datasets. Random Forest ranks third overall, confirming that bootstrapped aggregation of decision trees reduces variance effectively. Logistic Regression, despite its simplicity, achieves a competitive AUC of 0.878, suggesting that the feature space is approximately linearly separable for a substantial portion of the student population. The Decision Tree baseline consistently underperforms due to its high variance when trained on individual splits.

B. Feature Importance Analysis

Feature importance was computed by averaging the normalized impurity-based importance scores across all 200 trees in the Random Forest component of the HEL framework. The top five most predictive features were: (1) previous semester GPA (importance = 0.231), (2) overall attendance percentage (0.187), (3) assignment submission rate (0.143), (4) mid-semester examination score (0.112), and (5) weekly LMS login frequency (0.089). Together, these five features account for approximately 76.2% of the total predictive power.

These findings have direct pedagogical implications. The dominance of attendance and submission regularity as predictors underscores the importance of consistent engagement throughout the semester, rather than last-minute effort. Interestingly, the LMS login frequency—a proxy for self-directed study behavior—emerged as the fifth most important feature, suggesting that digital engagement metrics captured by learning management systems carry meaningful predictive signal even after controlling for traditional academic metrics.

C. Effect of SMOTE on Minority Class Detection

To quantify the benefit of oversampling, the HEL model was evaluated with and without SMOTE on the training data. Without SMOTE, the macro-averaged Recall for the at-risk class dropped from 90.5% to 83.2%, while precision increased slightly to 92.4%. This precision-recall trade-off confirms that training

without oversampling biases the classifier toward the majority (non-at-risk) class. The SMOTE-augmented model provides more balanced error rates, which is essential in an educational context where false negatives (missing at-risk students) carry greater social cost than false positives.

D. Discussion

The results demonstrate that a stacking ensemble that combines diverse base classifiers with a meta-learner consistently outperforms each individual constituent. The performance gains are attributable to the complementary error profiles of the base classifiers: when SVM misclassifies a borderline sample, Random Forest or XGBoost may classify it correctly, and the meta-learner learns to defer to the more confident classifier. This diversity-based error correction is the fundamental mechanism underlying the superiority of ensemble methods.

A practical limitation of the proposed approach is the increased computational cost relative to single classifiers. Training five cross-validated base models and a meta-learner requires approximately 2.1 seconds per run on a standard CPU, compared to 0.42 seconds for a single Decision Tree. While this overhead is negligible for offline batch prediction, it may necessitate optimization (e.g., parallelization, model distillation) for real-time deployment at scale. Future work will investigate the integration of temporal features derived from weekly LMS logs, drawing inspiration from sequence-based approaches such as Attn-ANN [9], to capture longitudinal learning dynamics within the ensemble framework.

V. CONCLUSION

This paper presented a Hybrid Ensemble Learning framework for student performance prediction that integrates five heterogeneous base classifiers through a stacking strategy. Evaluated on a 2,400-student dataset with 14 engineered features spanning academic, attendance, behavioral, and socioeconomic domains, the proposed model achieves 91.7% accuracy and an AUC of 0.942, significantly outperforming each individual baseline classifier. Feature importance analysis highlights attendance, prior academic achievement, and digital engagement as the strongest predictors of student success, providing actionable insights for educational practitioners.

The findings reinforce the value of combining diverse learning algorithms to exploit complementary predictive strengths, and of addressing class imbalance through SMOTE to ensure equitable detection of at-risk students. Future research will extend the framework by incorporating temporal sequence modeling of weekly LMS activity logs, exploring explainability methods such as SHAP values, and validating the model across multiple institutions and disciplines to enhance generalizability.

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SECURE AND TRUSTLESS CLOUD DATA SHARING USING BLOCKCHAIN, IPFS AND CRYPTOGRAPHIC ACCESS CONTROL

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ABSTRACT- *In the modern world of digital transformation, cloud storage has become an important aspect of data management. However, the security and privacy issues associated with centralized cloud storage are major challenges. Some of the issues include data breaches and unauthorized usage. In the traditional approach, data is stored in a single location. This creates security and privacy issues. In this research, a decentralized approach has been proposed for the secure and private sharing and storage of data. For this purpose, blockchain technology and InterPlanetary File System (IPFS) have been combined with advanced cryptographic techniques such as Elliptic Curve Cryptography (ECC), proxy re-encryption, and zero-knowledge proof. With the help of this proposed framework, users will be allowed to have full control over their data. For this purpose, the data will be stored in the IPFS after encryption. The metadata and authorization will be maintained by the blockchain. Proxy re-encryption and zero-knowledge proof will also be used for the sharing and verification of data. The technique eliminates points of failure, improves confidentiality and integrity, and offers a transparent and trustless mechanism for access control. This paper has shown that the challenges facing cloud security can be addressed through the use of decentralized technologies while at the same time giving the users a sense of ownership and privacy.*

KEYWORDS: *Access Control, Blockchain, Cloud Storage, Decentralization, Elliptic Curve Cryptography, IPFS, Zero-Knowledge Proof*

I. INTRODUCTION

The recent surge in the popularity and implementation of cloud computing technology has revolutionized the way in which data is shared and accessed. Although this technology is convenient for both personal and organizational use, the centralized nature of cloud computing poses major problems in relation to security, privacy, and data ownership. This is because critical information such as user credentials, access records, and personal data is typically stored in a centralized manner in the hands of a third party. This centralized system is a major threat in itself as it increases the probability of breaches in the system. Moreover, this system does not grant users much freedom in relation to their own data. A recent innovation in the field of blockchain technology and InterPlanetary File System (IPFS), coupled with the implementation of advanced cryptographic techniques such as Elliptic Curve Cryptography (ECC), proxy reencryption, and zero knowledge proofs, provides an effective solution for solving the problems faced by centralized cloud computing. This paper proposes a comprehensive system that leverages these innovations to ensure secure, efficient, and transparent cloud data management, empowering users with complete ownership and control over their digital assets.

i) Problem statement

Centralized cloud storage systems are the norm for data management and storage. However, such systems pose serious security and privacy issues. For instance, user credentials and other data are stored in the cloud. This creates a single point of failure. There are chances of data breaches and unauthorized use. Also, the involvement of cloud service providers creates issues of trust and transparency. The existing security protocols for data access are also not flexible. For instance, the use of tokens and session expiration and revocation are not transparent. This creates issues of Misconfigurations. Moreover, the centralized cloud storage system does not support the increasing requirements for scalability and privacy preservation. For instance, the users are not allowed to implement their own data access policies. Also, the integrity of the data is not preserved. Traditional encryption methods, while effective for securing data in transit, fail to

provide efficient and verifiable sharing mechanisms without exposing sensitive keys. This research addresses these limitations by proposing a decentralized framework that leverages blockchain, distributed file storage through IPFS, and advanced cryptographic techniques such as Elliptic Curve Cryptography (ECC), proxy re-encryption, and zeroknowledge proofs. The framework aims to eliminate single points of failure, enhance privacy, and empower users with full ownership and control over their data.

ii) Dataset details

The framework does not require a pre-existing dataset in a traditional sense, as it is designed for secure storage, sharing, and access control of user-generated content in a

cloud storage system. In order to conduct experimental validation, test files of various types and origins, both synthetic and real-world, are used to simulate user data in a variety of scenarios. Each file is encrypted using Elliptic Curve Cryptography (ECC) and then uploaded to the InterPlanetary File System (IPFS), with associated metadata such as file hashes, permissions, and transaction logs recorded on a blockchain database. The dataset supports various user cases and scenarios, such as authorized sharing and revocation, as well as verification mechanisms using zero-knowledge proofs. This allows for a comprehensive evaluation and testing of security and privacy in a real-world scenario and usage pattern in various types of cloud storage systems and applications. **iii) Objectives**

The main goal of this study is to propose a decentralized and privacy-preserving framework for safe and secure data storage and sharing in a cloud system. The framework will be designed in such a manner that it will avoid single points of failure by distributing data across the InterPlanetary File System and will utilize a blockchain system for maintaining metadata and access logs in order to provide immutable and verifiable authorization. Moreover, it will provide better security for data integrity and confidentiality by utilizing Elliptic Curve Cryptography and will provide a secure framework for data sharing between users by utilizing proxy re-encryption. In this study, zeroknowledge proofs will be used in order to provide users with a framework that allows them to verify access rights without revealing sensitive credentials. The main goal of this study is to provide users with a framework that gives them full control and power in order to combat cyber threats in a transparent and trustless manner.

II. RELATED WORK

A blockchain-based electronic medical record framework, which utilizes proxy re-encryption and multisignature technologies, was also proposed by Liu, Xiaoguang, Yan Jun, Shan Shuqiang, and Wu Rongjun [1]. This framework allows patients to control their electronic medical records, while also providing healthcare providers with access to the relevant data. This is achieved through proxy reencryption, which allows patients to share their electronic medical records with other users without disclosing their private keys. This is further secured by the multisignature authentication technology, which prevents unauthorized access. The use of a blockchain also ensures the immutability, traceability, and transparency of any transaction. This research proves that electronic medical records can be managed in a decentralized manner, thus protecting the data from risks of breaches, as well as from internal malicious users. The results of the performance evaluation also show that the encryption and sharing of electronic medical records can be done with minimal computational cost.

In another research paper, Alabdulatif, Abdullah, Navod Neranjan Thilakarathne, and Kassim Kalinaki [2] have suggested a cloud-enabled access control model that ensures the security and privacy of large-scale medical data. This model is based on attribute-based encryption and role-based access control. This ensures that only authorized users have access to medical data. Additionally, this framework is based on a hierarchical key management system that facilitates the efficient process of granting and revoking access for multiple users across distributed cloud servers. This is possible through the implementation of cloud computing along with cryptographic techniques. This framework also ensures the requirements for ensuring compliance in the context of healthcare data management. This is possible through the implementation of a framework that ensures transparency in data access while minimizing the probability of data disclosure. This study emphasizes the importance of integrating cloud infrastructure with robust access control policies for secure medical data handling.

Dhinakaran, D., et al. [3] have carried out a thorough survey on privacy-preserving data management in IoTbased cloud systems, specifically incorporating artificial intelligence techniques into it. The survey states various issues faced by centralized cloud systems that manage IoT data, such as security attacks like unauthorized access, data leakage, and manipulation. It also presents various types of encryption techniques and safe data aggregation techniques that have been proposed to provide security and privacy in such systems. In addition, it presents various techniques that use artificial intelligence for anomaly detection and predictive security techniques that provide security and privacy to IoT data. Moreover, it presents various techniques that use blockchain and distributed ledger technology to provide security and privacy in IoTbased cloud systems. The survey states that incorporating artificial intelligence techniques into IoT-based cloud systems provides a promising solution to tackle security and privacy issues faced by such systems.

Wang, Weizheng, et al. [4] presented a token system based on smart contracts to achieve privacy-preserving access control in industrial Internet of Things (IIoT) scenarios. This system uses blockchain technology to implement smart contracts that can automatically verify access control, record logs, and revoke access rights while maintaining the privacy of industrial data. Tokens are used to represent access rights, which can be safely transferred or revoked according to certain rules, greatly reducing the reliance on central authorities. This framework also includes encryption and auditing functions to ensure data confidentiality, integrity, and accountability. Simulation results show that this token-based access control system can achieve scalability, tamper-resistance, and efficiency in managing user permissions in industrial scenarios. This paper also discusses how smart contracts can help achieve fine-grained access control while ensuring transparency, which can provide a safe and trustless operating environment for industrial Internet of Things scenarios.

Alsuqaih, Hanan Naser, et al. [5] presented an efficient control mechanism in a privacy-preserving manner through a blockchain technology solution to e-health systems. This method involves a combination of lightweight encryption, distributed storage, and a blockchain technology solution to log data, which ensures the security of patient data while allowing access to authorized healthcare providers. This system ensures the immutability of patient data, as well as the auditing of all transactions, through cryptographic solutions such as proxy re-encryption to allow data sharing in a secure manner. This solution has shown that a blockchain technology solution can provide a solution to e-health systems, addressing issues such as trust, transparency, and compliance to regulatory requirements through a

decentralized system. Overall, this research highlights the potential of combining blockchain with advanced cryptography to enhance security and privacy in sensitive digital environments.

Kotha, Sita Kumari, et al. in their paper "A comprehensive review on secure data sharing approaches in cloud computing" have discussed in detail the various data sharing approaches that are used for securing the data in cloud computing. This paper discusses the various encryption techniques and access control methods that are used for securing the data in cloud computing. It also discusses the challenges faced in traditional cloud computing for securing the data. The paper also highlights the need for using blockchain technology for securing the data in cloud computing. In this paper, the authors have discussed the need for using blockchain technology for securing the data in cloud computing. The paper also highlights the challenges faced in traditional cloud computing for securing the data. The challenges include scalability and auditing. The paper also highlights the need for using blockchain technology for securing the data in cloud computing. Overall, the research provides a critical understanding of current methods and proposes directions for improving privacy, efficiency, and resilience in cloudbased data sharing.

Gupta, Ishu, et al. [7] carried out a systematic review of the existing methodologies of secure data storage and sharing in cloud environments. The review discussed the existing methodologies, their advantages, and their limitations. The review indicates that, although traditional centralized approaches offer ease of administration, they are not secure and may lead to data breaches. The review highlights the potential of blockchain technology and data encryption in addressing the challenges of cloud data storage and sharing. Additionally, the review indicates potential areas of future research in the field of cloud data storage and sharing. The potential areas of future research include the development of lightweight cryptography algorithms and the need for robust cloud data storage and sharing security frameworks. The review

indicates the potential of blockchain technology and data encryption in addressing the challenges of cloud data storage and sharing.

In another research paper by White, Tonya, Elisabet Blok, and Vince D. Calhoun [8], the challenges faced in sharing data and ensuring privacy in neuroimaging studies have been investigated. This paper emphasizes the need for ensuring strict privacy-preserving requirements for sharing biomedical data among research organizations. It also highlights the technical and ethical challenges faced in sharing data due to differences in formats, lack of standard encryption techniques, and inadequate access control policies. At the same time, this paper also emphasizes the potential benefits that blockchain technology can offer in ensuring data integrity and accountability in sharing data for collaborative research. Furthermore, it also emphasizes the need for clear consent policies, sharing policies, and data usage policies for ensuring overall data privacy.

Athanere, Smita, and Ramesh Thakur proposed a hierarchical semi-decentralized framework based on blockchain technology and incorporates IPFS for data sharing in a secure and efficient manner. In this framework, a hierarchy of clusters is created in which each cluster is responsible for local storage and access control. Blockchain technology is used to provide global auditability. In this framework, IPFS is used to store encrypted files in a distributed manner to provide fault tolerance and availability. In this framework, proxy reencryption and advanced encryption techniques are used to provide secure data sharing for authorized users without revealing the private keys. The experimental results show that this framework provides scalability, low latency, and security compared to a fully centralized cloud system. It proves that semi-decentralized models provide security and efficiency and resolve the issues faced by cloud storage systems.

Prajapati, Priteshkumar, and Parth Shah, in their paper [10], discussed secure data deduplication techniques to address issues related to storage efficiency and security, especially in cloud computing environments. The paper discusses issues related to unauthorized access while eliminating redundant data, which can lead to leakage of sensitive data if not properly handled. Various encryption techniques, such as "convergent encryption," have been discussed to ensure secure data deduplication. At the same time, issues related to security, such as unauthorized access, have been discussed, showing how data deduplication, though efficient, is not secure. Various solutions have been discussed, such as using encryption techniques with decentralized data storage and blockchain, to ensure secure data deduplication while preserving data privacy.

III. EXISTING METHODLOGY

In general cloud storage and sharing systems, centralized architectures are primarily used for managing and controlling data. In such systems, a central server or a central authority, such as the cloud provider itself, manages user authentication and access control in conjunction with storage resource allocation. In such systems, techniques such as symmetric and asymmetric encryption are generally used for data protection during transmission and storage. Other techniques such as session tokenization, password-based authentication, and access control lists are also used in such systems for managing access control and user authentication. However, such systems are heavily dependent upon the reliability and trustworthiness of the central server and are therefore prone to security attacks and violations. In centralized systems, a single point of failure is a major issue because all sensitive information, including user authentication and access control data, is centrally stored in a single repository. In case of a server attack or violation, a large amount of data is at risk of being compromised or attacked. Furthermore, these systems heavily depend on trust with third-party providers, which makes the level of transparency in data management and sharing unclear. The level of control that users have in these systems is minimal, while the process of key management, expiration, and revocation is unclear, which makes the systems vulnerable to unauthorized access as well as data loss. The main reason these systems are a threat is that they are used in applications that require confidentiality as well as user autonomy. In addition, traditional cloud storage systems are vulnerable in terms of scalability, interoperability, as well as the preservation of privacy. With the increase in the amount of data, the centralized server acts as a bottleneck, causing the systems to become inefficient. The existing methods are unable to offer efficient mechanisms for the secure sharing of files among multiple users without revealing the sensitive encryption keys as well as the credentials of the

users. In addition, the verification of user access rights involves the interaction of the user with the central authority, which makes the systems vulnerable in terms of privacy, causing the user to lose trust. Overall, while current techniques offer basic data protection, they are insufficient to meet the evolving requirements of modern cloud applications, highlighting the need for a decentralized, cryptographically secure alternative.

IV. PROPOSED METHODOLOGIES

The proposed system incorporates a decentralized system that ensures data security, privacy, and control in a cloudbased system. Instead of relying on a central authority to control data security and privacy in a cloud system, this framework uses a blockchain system that records metadata and access permissions in a tamper-resistant and immutable way. Data is encrypted using Elliptic Curve Cryptography (ECC) and then stored in a decentralized system called InterPlanetary File System (IPFS). This system ensures that data security and privacy are guaranteed by eliminating a single point of failure and relying on a third party to provide storage and access control services. Moreover, proxy re-encryption is incorporated in this system to ensure that users have access to encrypted data without having access to the actual encryption keys. This allows users to control access to sensitive data and maintain privacy. In this system, zeroknowledge proofs are also used to ensure that users are authorized to access data without having access to sensitive credentials. The combination of ECC, proxy re-encryption, and zero-knowledge proof offers a multi-layered security system that allows only authorized users to access the data while the entire system is transparent and traceable on the blockchain. The system is intended to be scalable, robust, and user-centric. IPFS offers the benefit of distributed data storage among various nodes, thus increasing fault tolerance and data availability. On the other hand, the use of blockchain offers data integrity. Users are given full control over data sharing and access. This allows users to have full control of data without the involvement of a central entity. The proposed system has the potential to solve the problems associated with traditional cloud storage systems by the use of advanced cryptography and the integration of other technologies such as decentralization.

METHODOLOGY

Data Encryption Using Elliptic Curve Cryptography (ECC)

Files generated by users are encrypted with Elliptic Curve Cryptography, which provides strong security with smaller key sizes compared to traditional asymmetric encryption. ECC ensures that data remains confidential during storage and transmission while reducing computational overhead, making it suitable for cloud environments where efficiency is crucial. Each file is uniquely encrypted, and the corresponding encryption keys are securely managed by the data owner.

Decentralized Storage with IPFS

Encrypted files are stored on the InterPlanetary File System (IPFS), a distributed file storage network that ensures tamper-resistant and immutable storage. IPFS divides files into smaller blocks, distributes them across multiple nodes, and generates unique content-based hashes for each file. This approach eliminates reliance on a central server, increases fault tolerance, and allows fast retrieval from any node in the network.

Access Control with Blockchain

Metadata, including file hashes, access permissions, and transaction logs, is recorded on the blockchain to provide transparent, verifiable, and immutable access control. Blockchain ensures that all access attempts, permission grants, and revocations are permanently logged, allowing users to audit and verify interactions without depending on a central authority.

Secure Sharing via Proxy Re-Encryption

Proxy re-encryption allows encrypted files to be securely shared with authorized users without revealing the original encryption keys. The data owner can grant or revoke access efficiently, ensuring that only legitimate users can decrypt the shared content. This mechanism enhances flexibility in multi-user environments while maintaining data confidentiality.

Privacy Preservation with Zero-Knowledge Proofs

Zero-knowledge proofs (ZKPs) enable verification of user authorization without disclosing sensitive credentials. This mechanism ensures that access rights can be validated by the system or third parties without revealing the underlying encryption keys or personal information, enhancing privacy and trust in a decentralized environment.

System Workflow Integration

The overall workflow integrates encryption, decentralized storage, blockchain-based access control, proxy reencryption, and zero-knowledge proofs into a unified system. This integration ensures that data remains secure, verifiable, and private at every stage, empowering users with full control over storage, sharing, and access management.

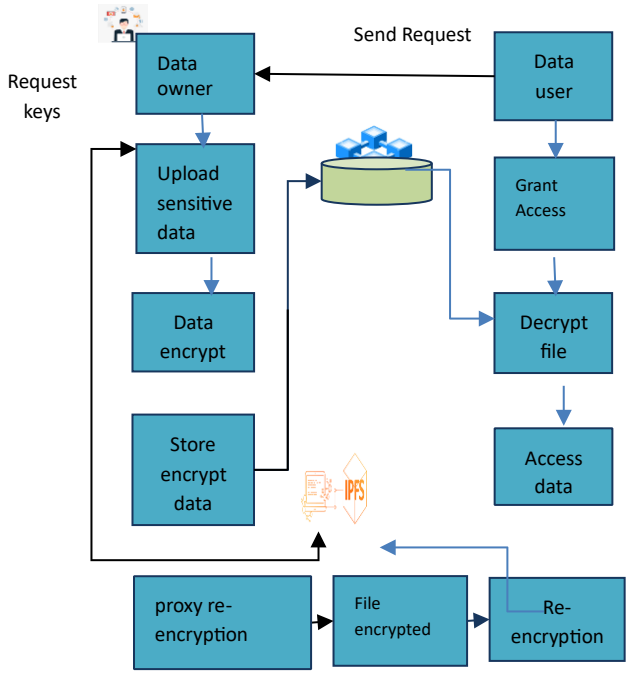

Figure 1: Diagram representation of the proposed Methodology

V. EXPERIMENTAL RESULTS

To test the efficacy of the suggested decentralized system, experiments were carried out using various test files, such as documents, images, and multimedia files. Performance parameters such as data security, transparency of access control, encryption/decryption efficiency, fault tolerance, and data privacy were considered while evaluating the system. At the same time, the existing centralized cloud computing system was tested. Based on the experiments, it is found that the suggested system excels in all aspects compared

to conventional methods using techniques such as blockchain, IPFS, Elliptic Curve Cryptography, proxy re-encryption, and zero-knowledge proofs. To prove the efficacy of encryption/decryption using Elliptic Curve Cryptography, experiments were conducted using files of various sizes, showing high security with low computation time. IPFS-based data storage improved fault tolerance, minimizing system downtime compared to a centralized system. Blockchain-based access control ensured transparency of access permissions. In addition, proxy reencryption and zero-knowledge proofs improved file sharing security. Overall, the proposed system provides a trustless, privacy-preserving, and efficient environment for cloud data management.

Performance Metric	**Existing System**	**Proposed System**
Data Confidentiality	5	9
Access Control Transparency	3	9
Encryption/Decryption Efficiency	5	8
Fault Tolerance / Availability	4	9
Privacy Preservation	3	9
Scalability	5	8
Auditability / Traceability	3	9

Table 1: Comparative Performance Metrics (Existing vs Proposed System)

The results indicate that the proposed system significantly enhances security, privacy, and reliability compared to traditional centralized cloud storage, making it suitable for modern applications requiring trustless and verifiable data management.

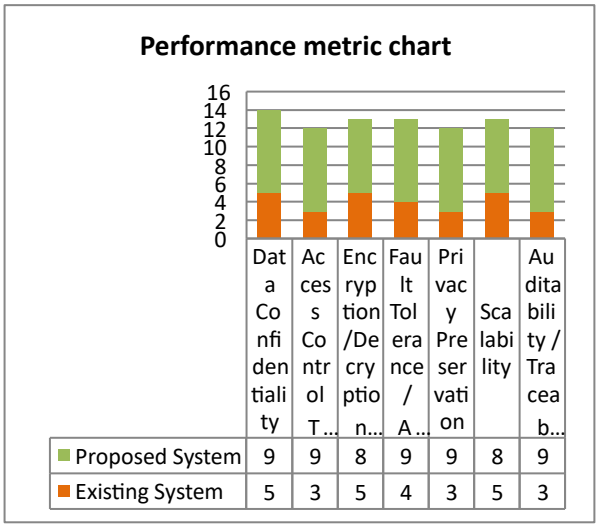

Figure 2: Performance metric chart representation

VI. CONCLUSION

The research proves that the integration of blockchain technology, IPFS, and other advanced cryptographic protocols such as Elliptic Curve Cryptography, Proxy ReEncryption, and Zero-Knowledge Proofs has the potential to improve the security, privacy, and controllability of data in cloud computing. The proposed system eliminates the dependency on central authorities and removes the single points of failure. The experimental results show significant improvements in the confidentiality, privacy preservation, fault tolerance, and empowerment of data in the cloud compared to the traditional centralized cloud storage system. The proposed system enables the sharing of files among the authorized users securely and preserves the privacy and confidentiality of the data while minimizing the chances of unauthorized access. Moreover, the decentralized system provides a robust solution for modern cloud-based applications. It allows the users to have full control and ownership of the data. The integration of ECC, IPFS, blockchain technology, and other privacy-preserving protocols creates a trustless environment for the management of sensitive data. Overall, this research highlights the potential of decentralized technologies to address the inherent limitations of traditional cloud storage, establishing a robust, privacy-preserving, and user-centric model for secure data storage, sharing, and access management in digital ecosystems.

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RESEARCH ARTICLE

GATE PING: IoT-Based Railway Level Crossing Monitoring and Route Guidance System Using ESP32

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Abstract

Railway level crossing is highly prone to accidents due to delayed gate closure, human error, and lack of monitoring in real-time. This paper proposes a smart railway level crossing monitoring and navigation system using IoT technology. This smart level crossing monitoring and navigation system is named GATE PING. This smart level crossing monitoring and navigation system is implemented using ESP32 microcontrollers and magnetic sensors at strategic distances from the level crossing. One sensor is placed 6 km before the level crossing to send alerts to the web platform. Another sensor is placed 2 km before the level crossing to close the gate using a servo motor. Another sensor is placed 1 km after the level crossing to open the gate using a servo motor. This smart level crossing monitoring and navigation system also provides users with the shortest routes and level crossings through its web platform like a navigation system. In addition, if the gate is closed at a level crossing, it provides users with alternative routes.

Keywords: Internet of Things (IoT), Smart Railway Level

24 Crossing , Automated Gate Control , Real-Time Monitoring

25 , Smart Transportation Systems .

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1 Introduction

Railway level crossings are identified as accident-prone zones due to delayed gate closure, human factor, and lack of information for road users. Many of these crossings are still operated manually or semi-automatically, which may not respond promptly to the approaching trains. Hence, there is a need for an intelligent and automated monitoring system for these railway level crossings.

The paper proposes an Internet of Things-based smart railway level crossing monitoring and navigation system, GATE PING. The system utilizes ESP32 microcontrollers and magnetic sensors installed at different distances from the crossing to detect the approaching trains and control the gates automatically. A sensor installed 6 km before the gate sends an early alert via a web platform, while another sensor installed 2 km before the crossing operates the gate automatically. A sensor installed after the crossing operates the gate to open it for the departing trains.

The system offers a web platform to display the shortest path and alternative paths in case of closure of the gate, thereby ensuring the safety of the road users and avoiding traffic congestion.

2 Related Work

Research has been carried out to improve the level of safety at railway level crossing points using automation and IoT technologies. For instance, an automatic

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control system of a railway gate using Arduino and ultrasonic sensor technologies has been proposed to improve safety at level crossing points. The system is able to detect the arrival of a train at a level crossing and close the gate using a servo motor.

Another research has proposed an IoT-based automatic system of a railway level crossing. In this system, sensors are used to detect the arrival of a train at a level crossing and send notifications to a central server. Such a system has greatly improved the level of safety at level crossing points.

Furthermore, IoT-based systems have been developed to monitor rail conditions and detect any faults using sensor technologies connected to cloud platforms. Although such systems have greatly improved the level of safety at level crossing points, they have not provided any support to drivers who use level crossing points to navigate through such points.

3 Methodology

The GATE PING system, which is being proposed, is based on IoT devices, sensor-based train detection, and a web platform. The system is based on an ESP32 microcontroller, which has inbuilt Wi-Fi capability and can transmit data to a web server. Three magnetic sensors are fixed at varying distances from the railway gate. The first sensor is fixed 6 km before the gate and detects the arrival of a train, sending a message to the web platform. The second sensor, fixed 2 km before the gate, automatically closes the gate using a servo motor. The third sensor is fixed 1 km after the gate and detects the arrival of the train, sending a signal to automatically open the gate.

Users can access this system using their mobile devices and can input their source and destination. The system will then use Dijkstra's algorithm to provide users with the shortest path and an alternate path if the gate is closed.

4 Experiments

Algorithm 1: Smart Railway Gate Monitoring and Route Guidance Algorithm

Data: Magnetic sensor signals, user route request
Result: Gate automation, alerts, and route guidance
Initialize ESP32 with Wi-Fi connection; Initialize LCD display, buzzer, and servo motor; Connect ESP32 to web server;
while *system is running* **do**

Read Sensor 1 (6 km before crossing);
if *train detected* **then**

Activate buzzer for warning;
Display "Train Approaching" on LCD; Send alert to web server;
end

Read Sensor 2 (2 km before crossing);
if *train detected* **then**

Close railway gate using servo motor; Display "Gate Closed" on LCD; Update gate status on web platform;
end

Read Sensor 3 (1 km after crossing);
if *train detected* **then** Open railway gate; Stop buzzer;

Display "Gate Open" on LCD; Update gate status on web platform;
end

if *user requests route from mobile/web* **then** Apply Dijkstra's shortest path algorithm; Check gate status;

if *gate is closed* **then**

Suggest alternative route;
end

Display route and crossing status on web dashboard;
92

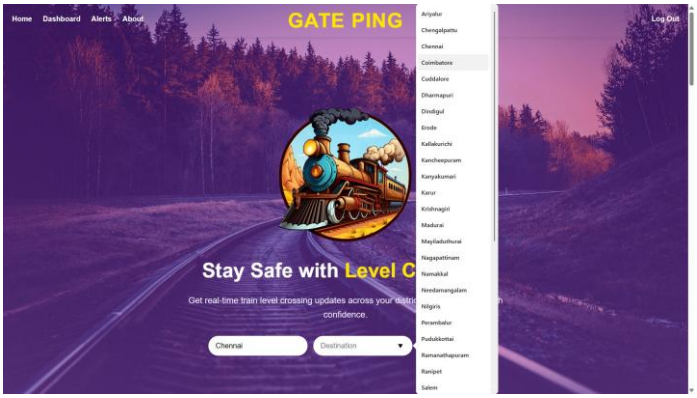

Figure 1. Source and destination route selection showing railway level crossings.

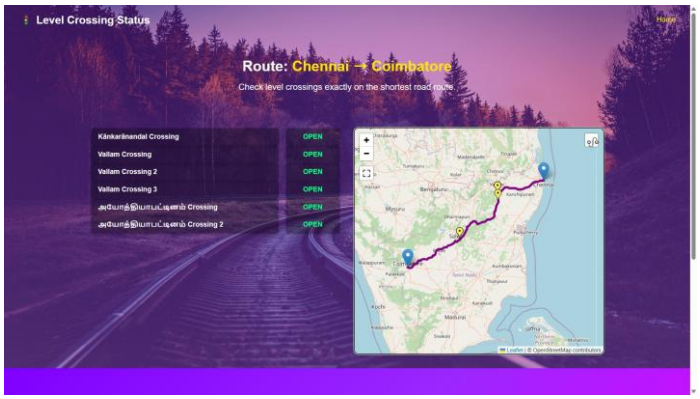

Figure 2. Web dashboard showing railway gate status.

it through the web dashboard via ESP32's Wi-Fi capabilities. The LCD display indicated "Train Approaching," and the buzzer was used to notify people around the crossing.

In another experiment, the sensor placed 2 km before the crossing successfully closed the railway gate using a servo motor. This was successfully updated on the web platform, enabling users to see the closed gate in real-time.

Lastly, the sensor placed after the crossing successfully detected the train's passage and opened the gate. The web platform was used to confirm its usability on various devices such as mobile phones.

Table 1. System performance accuracy analysis.

System Module	Accuracy
Train Detection	0.97
Gate Closing Mechanism	0.96
Gate Opening Mechanism	0.97
ESP32 Wi-Fi Communication	0.95
Route Navigation Algorithm	0.96
Alternative Path Suggestion	0.95

Figure 3. Route navigation interface showing railway gate locations and status.

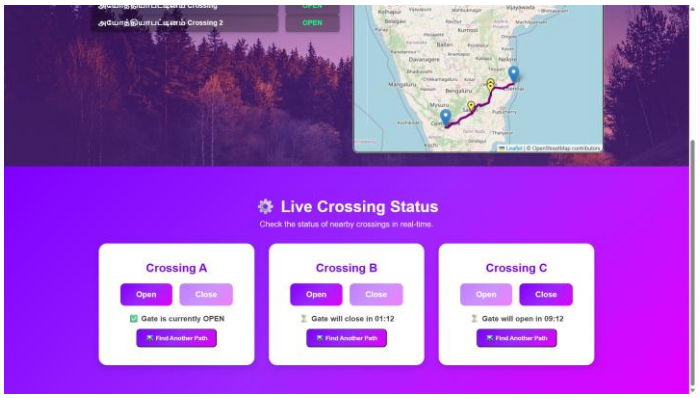

Figure 4. Navigation interface displaying the railway level crossing status and suggesting an alternative route.

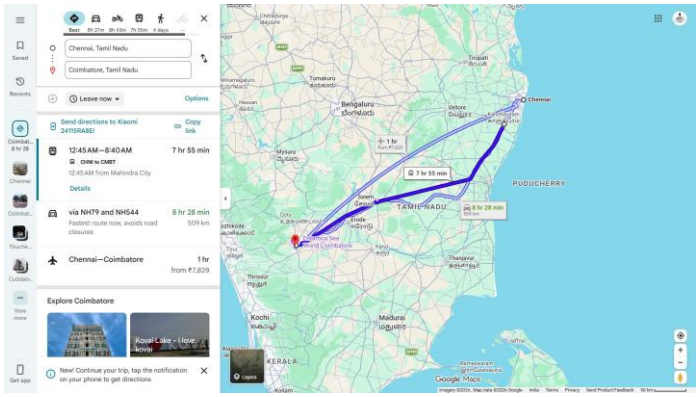

Figure 5. Alternative route suggested when the railway gate is closed.

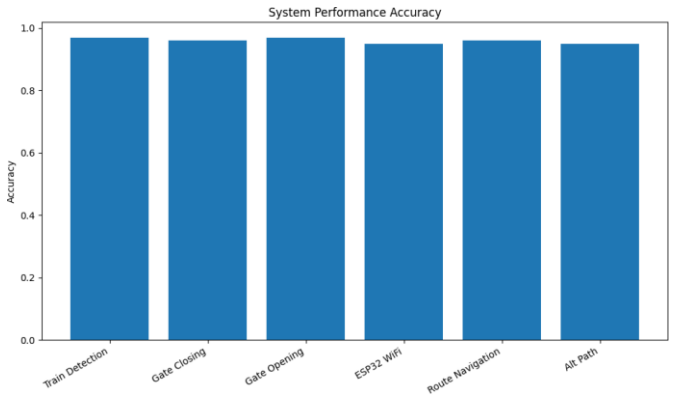

Figure 6. Accuracy analysis graph of the proposed railway gate monitoring system.

4.1 IoT Hardware and Software Implementation

The proposed GATE PING system is implemented using IoT hardware components such as an ESP32 microcontroller, magnetic sensors, servo motor, LCD display, and buzzer. The ESP32 acts as the main controller of the system and processes signals received from the sensors. The system is programmed using Embedded C in the Arduino development environment.

Magnetic sensors are installed at different distances from the railway crossing to detect approaching trains. When the train reaches the first sensor placed 6 km before the crossing, the sensor sends a signal to the ESP32. The ESP32 processes this signal and transmits an alert to the web server through its built-in Wi-Fi module. At the same time, the LCD display shows a warning message and the buzzer is activated.

When the train reaches the second sensor located 2 km before the crossing, the ESP32 triggers a servo motor to automatically close the railway gate. After the train passes the crossing and activates the third sensor placed 1 km after the gate, the ESP32 sends a signal to open the gate automatically.

The system also updates the gate status on the web platform, allowing users to monitor railway gate conditions and select alternative routes through mobile devices. The overall system architecture of the proposed railway level crossing monitoring and route guidance system is shown in Fig.

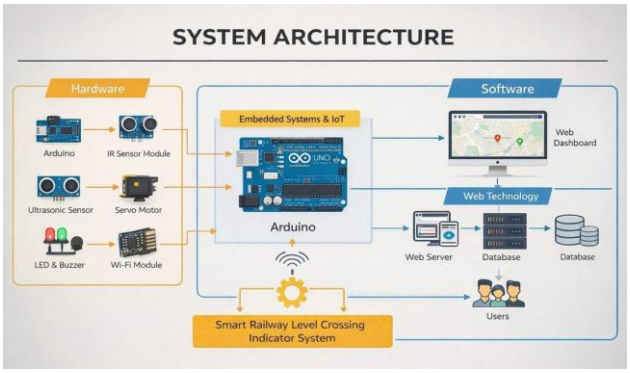

Figure 7. System architecture of the proposed ESP32-based railway level crossing monitoring and route guidance system. The architecture illustrates communication between sensors, ESP32 controller, cloud platform, and web/mobile application for real-time monitoring and navigation support.

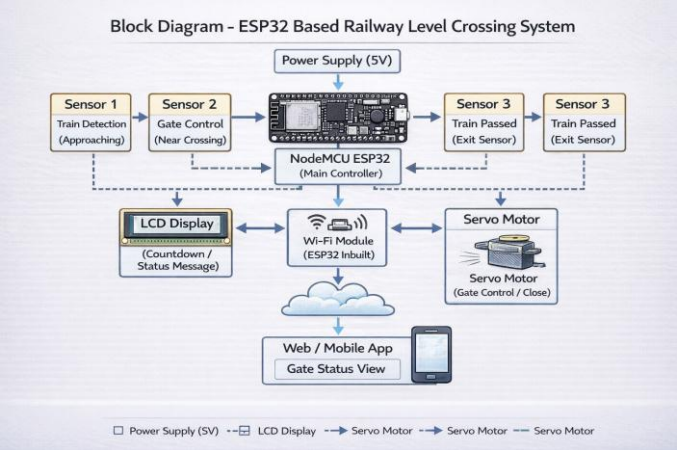

Figure 8. Block diagram of the proposed ESP32-based railway level crossing monitoring and route guidance system. The system integrates train detection sensors, ESP32 microcontroller, servo motor gate control, LCD display, and Wi-Fi communication for real-time monitoring and user navigation support.

The hardware pin connections of the ESP32 microcontroller used in the system are illustrated in Fig. 9.

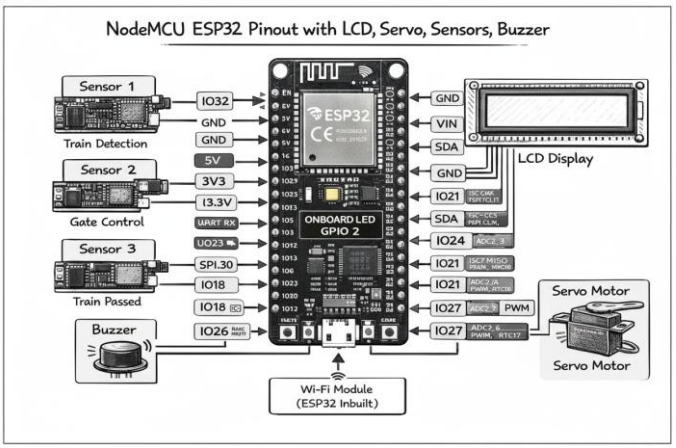

Figure 9. ESP32 NodeMCU pin configuration illustrating the connections with train detection sensors, LCD display, servo motor, and buzzer used in the proposed railway level crossing monitoring system.

4.2 Manual Control Using Web Interface

Besides the automatic control of the system, another feature of the proposed system is the provision of a manual control option through a web interface. The ESP32 controller sends and receives data to and from the web server via its Wi-Fi module. This enables data exchange between the IoT devices and the web application in real-time. Through this option, users can access and control the status of the railway level crossing gate manually.

The web interface shows the status of the railway gate, indicating whether it is open or closed. Upon receiving the control request through the web interface, it is forwarded to the ESP32 controller. The controller then sends a signal to the servo motor to perform the desired action.

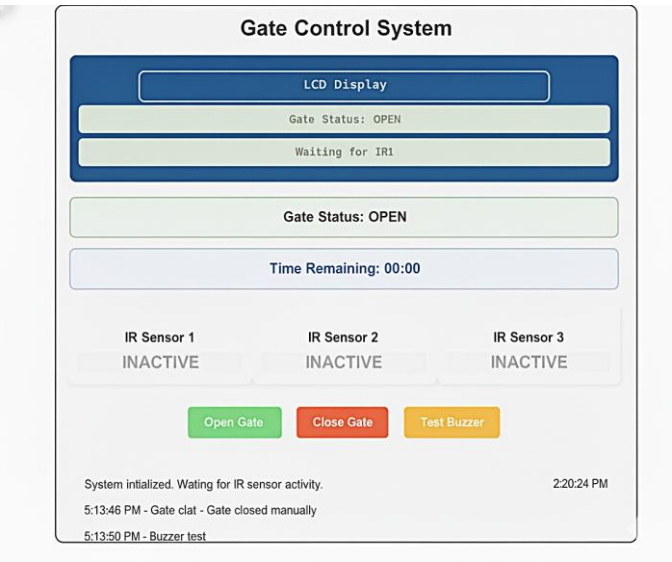

Figure 10. Web-based interface for monitoring railway level crossing status and manually controlling the gate operation in real time.

4.3 Integration of Maps with OpenStreetMap and Google Maps API

The proposed system would incorporate mapping services for providing navigation support to users. Open Street Map is used for displaying geographical information and railway level crossing locations. Through this map interface, users can view railway

JavaScript. The backend system communicates using REST-based APIs. The ESP32 IoT device is programmed using Embedded C and the Arduino IDE. The Arduino IDE is efficient in interacting with IoT devices and communicating with the backend system.

Moreover, this system is integrated with various mapping-based services using OpenStreetMap and Google Maps API to provide users with navigation assistance based on the status of the railway gate. The backend server processes the sensor data and updates the status of the railway gate in real-time. The users can view the updated status and navigate accordingly using the suggested routes based on the status of the gate.

5 Results and Discussion

The performance of the proposed ESP32-based railway level crossing monitoring and route guidance system has been evaluated through several experimental tests. The system has been tested under different operating conditions to check the functionality of the proposed system.

During the course of conducting the experiments, the magnetic sensor has been able to detect the presence of the approaching train and send the corresponding signal to the ESP32 microcontroller. Depending upon the received signal, the ESP32 has been able to automatically close the railway gate using the servo motor. Once the train has crossed the railway crossing and activated the exit sensor, the ESP32 has been able to automatically open the railway gate.

The system also updated the status of the railway

In addition, the Google Maps API is used for calculating routes between the selected source and destination locations. In case it is identified that the railway gate is closed, another route is suggested using the routing option of the Google Maps API.

4.4 Backend Integration of IoT and Web Platform

The backend of the proposed system facilitates crossing and get navigation guidance if the railway gate is closed. The system can provide users with alternative routes between the selected source and destination using the OpenStreetMap and Google Maps API.

The experimental results show that the proposed system works well and can provide accurate monitoring and control of railway crossings. The communication between the ESP32 IoT device and the web-based monitoring system. The ESP32 communicates and transmits data to the backend server using Wi-Fi connectivity and HTTP-based communication protocols.

system can integrate IoT devices, web technologies, and navigation services to provide better safety and route planning assistance to users. The experimental results verify that the suggested system effectively detects the movement of the trains and controls thegate operation of the railway system. In addition, the integration of IoT technology with web-based navigation services increases the level of safety of all users on the road.

6 Conclusion

In the paper, the authors have discussed the IoT-based railway level crossing monitoring system with route guidance using the ESP32 microcontroller. The system is designed with a combination of magnetic sensor, servo motor gate control mechanism, LCD display, and wireless communication. The system can automatically sense the movement of the train and control the railway gate accordingly.

Further, the integration of Open Street Map and Google Map API allows users to get the location of the railway gate and alternative routes to the destination, even if the gate is closed. The experimental results demonstrate the effectiveness of the system, which improves the safety of the users. The system reduces the waiting time at the railway gate, thereby increasing the safety of the users.

Future Work

Future enhancements of the proposed system may also be made by incorporating GPS technology to accurately predict the arrival of trains at railway crossing points. Another method to enhance this system is to develop a mobile application to send notifications to users of the system.

Furthermore, it is also possible to use machine learning to accurately predict traffic on roads at railway crossing points. It is also possible to use additional sensors and cloud storage to enhance the reliability of this system. Such enhancements may enable this proposed system to be used to build large-scale smart infrastructure systems and develop intelligent railway safety systems.

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CURRENT TRENDS IN INDIAN EDUCATION SYSTEM - A REVIEW

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ABSTRACTS

The purpose of this study is to look into the current trends within the education system in India. This research uses a literature review approach, and content analysis is used to gather information. Education plays a vital role in a country like India, contributing to its development, economic growth, and social progress. It includes undergraduate, postgraduate, pre-doctoral, and doctoral programs. It is also essential for producing qualified teachers, which makes it crucial for the country's survival. Therefore, this study provides an understanding of the current trends in the Indian education system, the challenges it faces, and potential ways to enhance it. The study is based on a review of existing literature, and data was collected by searching online databases such as PubMed and Google Scholar using relevant keywords. Although higher education in India has seen significant growth in recent years, it still faces several challenges, including the quota system and increasing privatization. As a result, there is a need to explore various strategies to improve the higher education system in India.

Keywords: *Education System, Emerging trends, Higher Education, Teacher Education*

INTRODUCTION

A country like India needs education because it plays a crucial role in social transformation and development. For real change to happen, new innovations and current trends in education must be accepted by the people. This is important both in terms of quality and quantity. A critical evaluation of the system came to India with the appointment of the University Education Commission in 1948. Educational innovations are emerging in India to boost economic growth and to strengthen and protect democratic values, as well as to achieve equality, human rights, and women's rights, among other things (Kumar R., 2017). Innovation is generally defined as the introduction of new uses and techniques that are beneficial to society. Schools and institutions conduct experiments to overcome challenges and improve efficiency, as the responsibility of teachers in helping students realize their dreams, potential, and become responsible citizens has increased (Singh G., 2014). The traditional teacher-dominated classroom practices have shifted towards a partnership between teachers and their peers. Educational institutions have taken many initiatives to change both formal and informal forms of education. Naseem and Anas (2011) focused on various problems that exist in the present Indian education system. Sharma (2012) emphasized that ICT can play a major role in the growth of the teaching profession and in shaping the global economy. According to the 11th plan (2007 to 2012), India ranks second in the world in enrolling students for higher education. The 5th year plan (2012 to 2017) and beyond indicated that the Indian education system faced challenges in expansion, equity, and excellence. Therefore, there is a need to focus on individual intelligence or start self-financing courses to address these issues (Duraisamy et al., 2019). India has produced many great people in fields such as engineering, medicine, and research.

CURRENT TRENDS IN INDIAN EDUCATION SYSTEM - A REVIEW

In today's world, there is a high demand for skilled and educated individuals. Over the next few decades, India is expected to have the largest number of young people, who can be a significant asset if their potential for employment is fully realized. The Indian education system is among the top ten globally and plays a major role in supplying a large workforce through technical education. However, it faces several challenges, including low teaching quality, funding issues in higher education, privatization trends, the quota system, political interference, and the lack of moral values. While there has been some growth in the education sector, it is not enough, especially in a country like India (Selvan SR, and Ganapathy D; 2016). This growing trend is also reflected in the choices students make for their higher education. For a long time, students primarily aimed for careers in medicine, engineering, law, and accounting. While this trend still holds true, there is a gradual shift towards exploring new and more interesting career options due to the broadening of career choices. Educational applications are being developed to transform traditional textbook learning into an engaging experience through the use of images and videos, making the learning process more interactive and capturing students' imaginations. This study highlights the challenges that hinder these emerging trends in education and offers suggestions for improvement, alongside exploring other emerging developments in the field.

PRESENT SCENARIO

India has a large education system, but it includes many teachers who are not properly trained or committed to their jobs. This leads to problems like shallow training and teaching methods (Singh G; 2014). The current system is shaped by a mix of national and state goals, plans, and actions that are influenced by individual ambitions. Amartya Sen once quoted one of his teachers, saying, "the frustrating thing about India is that whatever you can rightly say about India, the opposite is also true" (Sen, 2005). This is also true for India's higher education system, which is continuously being asked to do more for a growing population (Stolarick, K; 2014). India is expected to become the world's largest country by the end of 2022. This demographic change could be a strong driver for growth and give India a significant advantage over countries with aging populations like China and the USA. However, India still has about a quarter of its population living in extreme poverty, and social inequality is increasing. So, it's still unclear whether India can effectively use its young population as a resource for growth (Ganapathy, et al; 2017). With 1.5 million schools, over 260 million students enrolled in higher education, and around 751 universities and 35,539 colleges, India has the largest education system in the world. It has also signed a credit agreement with the World Bank under the SANKALP program to improve the system for skill development. In this system, students are evaluated based on their academic grades through lab experiments and practical tasks included in the curriculum. However, these assessments don't hold much real value. Improving education infrastructure is a major focus in the current decade. The Indian government is also providing new scholarships for research scholars (Ashok V, Suvitha S.; 2016). Students are trained only to pass exams with good marks. Thinking creatively is not encouraged. They are not given the freedom to think independently but are just told to memorize lessons and repeat them in exams. India was expected to rank third in the world in education by the end of 2020, but the number of students pursuing education is low and not widely accessible due to quota systems and social divisions present in society (Ashok V; 2014).

REVIEW OF THE LITERATURE

Recently, several content analysis and meta-analysis studies have come out looking at educational research. These studies cover a range of topics, including general educational sciences (Goktaş, Hasançebi et al., 2012; Keselman et al., 1998), educational administration (Gulmez & Yavuz, 2016), educational technology (Goktaş, Küçük et al., 2012; Hrastinski & Keller, 2007), curriculum and instruction (Ozan & Köse, 2014), primary school teacher education (Küçükoğlu & Ozan, 2013), special education, language education (Varışoğlu et al., 2013), teacher education, mathematics education, environmental education (Erdogan,

Marcinkowski & Ok, 2009), preschool education (Yılmaz & Altıntürk, 2012), and science education (Tsai & Wen, 2005). These content analysis studies serve as a foundation for comparative research and help to identify current research trends (Cohen et al., 2005). Reviewing articles in academic journals is important for understanding the field and tracking its development (Gulmez & Yavuz, 2016). In addition, looking at international academic journals helps to spot global trends and changes, rather than just focusing on research from one country. In Turkey, the number of journals publishing educational research that are indexed in international educational databases has grown a lot recently (Yılmaz & Altıntürk, 2012). One such journal is the International Journal of Instruction. Founded in 2008 in Turkey, this journal aims to publish high-quality research in areas like instruction, learning, teaching, curriculum development, learning environments, teacher education, and educational technology. It is indexed in several databases (e-iji.net). As researchers from all around the world contribute to this journal, analyzing the articles published between 2008 and 2017 through content analysis could offer valuable insights into the topics, models, research designs, data collection tools, analysis methods, sampling approaches, participants, and countries involved in these studies. Therefore, this study seeks to use content analysis to examine the articles published in the International Journal of Instruction [IJI] during that time period.

RECENT TREND IN EDUCATION

The face of the Indian education system has completely changed due to new trends like artificial intelligence, personalized learning, wellness programs, and teacher training initiatives. These trends have allowed students and teachers to interact and give feedback to each other, making the learning process more engaging. Artificial intelligence, in particular, is considered a great investment (Arya, N; 2019). Digital trends have shifted the focus of education towards creativity and original thinking, similar to a do-it-yourself approach. Massive online courses are growing rapidly and are still developing. They ensure the curriculum stays at a high standard, which makes the learning experience better and helps students get exactly what they need from their education. However, the main challenge comes when these trends are put into practice. For newcomers, using them to their full potential can be difficult. There may also be less direct interaction, more time needed to get used to them, and a higher chance of dropping out (2. Sanklecha N). With the global market becoming more connected and cultural barriers disappearing, along with new policies of liberalization and privatization in higher education, the Government of India has seen the rise of various sectors in the economy. These fast-growing sectors are creating a demand for skilled, dynamic, and qualified workers. Considering this, many non-conventional and technical courses are now being introduced in general education and professional institutions across India (Kumar, R; 2009). There are many new trends in education, and it's hard to list and discuss them all. We have covered some of the major ones, but there are plenty more that are equally important. In this section, we'll mention a few of these trends so that you can learn more about them later.

Lifelong education: We find that today education is an ongoing process, and most people in any profession or occupation need to continue their education through formal, non-formal, and informal channels. The fast-growing body of knowledge requires individuals to keep up, which is why continuous learning is essential. Even those who are not in any particular profession may engage in educational activities at any age or stage in their lives. While education is often driven by personal or professional needs, the fundamental philosophy behind it is an open-minded approach that recognizes and responds to people's educational needs. Life-long education is made possible by advancements in information and communication technologies, as well as the opportunities provided by distance learning.

Open and distance learning (ODL): Today, educational opportunities are expanding and reaching millions through this method. It is now seen as a powerful driver for speeding up social and economic growth. This is a modern trend that is growing very quickly. According to the Knowledge Commission in higher education, about half of the learners are enrolled in this mode. This is made possible by new information and communication technologies. You might also know that the combination of traditional and

distance learning is becoming more common, and it is making the lines between the two systems blur. Students on campus might end up studying off campus and the other way around, or they could be getting benefits from both regular classroom teaching and learning from a distance.

Integration of ICT: The teacher is no longer the only source of information as technology is now acting as a substitute for the teacher. Advanced technologies such as computers and web-based tools are increasingly being incorporated into the educational system. These technologies are used not only for teaching and learning but also for educational management tasks like creating databases, maintaining records, and sharing information. Information and Communication Technology (ICT) is now seen as essential for improving the quality of education. Because of this, UNESCO launched the "ICT in Education Policy" project in 2003 to develop suitable policy models and strategies for integrating ICT into education across the Asia-Pacific region. This is due to the significant changes in communication systems, which have created new demands in the workforce, and learners need to be prepared to adapt to this new global environment.

Inclusive education: Children with special needs are often seen as people who need help and are treated with pity instead of respect. But this view doesn't recognize the big talents that these children have, which are not being used because they are pushed to the sides of society. In the best case, their needs are managed by certain schools that are meant specifically for them. However, since these schools are not enough, most children with special needs don't get proper education. Sending young children with disabilities to special schools is also not always seen as a good idea, because it makes other children think that those with special needs are different and should be taken away from the rest. The idea now is that schools should be like communities where everyone lives together in harmony. So, education should start by including all children, and if needed, special support can be given later. This approach, called inclusive education, aims to bring more children with disabilities into regular schools instead of leaving them out, so that everyone gets fair treatment and equal chances.

CONCLUSION:

Despite notable advancements in recent years, India's higher education system still faces risks due to challenges such as a relatively low gross enrollment ratio. Therefore, the focus should shift towards the overall development of individuals and the cultivation of multiple intelligences, rather than just emphasizing linguistic and logical intelligence. To better understand ongoing trends and patterns related to this issue, it is recommended that similar studies be conducted using a journal-based approach and repeated at least every five years.

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Consumer Preference in Multivendor E-Commerce Marketplaces: An Exploratory Perspective

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Abstract

E-Commerce Multivendor Marketplaces offer a variety of products to the consumer all sold on a single digital platform; while multivendor e-commerce marketplaces enhance accessibility, variety, and convenience, they also introduce significant complexity into the consumer decision-making process. The consumers often undergo heightened awareness, the benefits offered, many a times become a bane to completing the purchase. Consumers face issues such as information overload, quality validation, trust and most importantly the decision regarding vendor selection from among the many. For the sellers unless they understand and address these issues, acquiring and retention of customers looks grim. This paper brings to the fore an exploratory context regarding consumer preference in vendor selection when buying on e-commerce multivendor marketplaces.

Keywords: Consumer Behaviour Process, E-Commerce, Multivendor Marketplace, Consumer Preference, Consumer Behaviour Determinants

1. Introduction

1.1. Scaling Heights: The E-Commerce Sector

The internet heralded the ecommerce shopping movement, since the first online purchase in 1984 ecommerce has grown astronomically, the present growth rate since can be pegged at 400% in the timespan of 40 years. Figure 1 illustrates the growth of the e-commerce market; presently valued at $6.8 trillion, it is estimated to grow to $8 trillion by the year 2027 [1]. In comparison to some of the larger sectors such as oil and gas, and the manufacturing sector, e-commerce can be said to be an infant sector that has been on an accelerated growth trajectory[2]. The global economy is undergoing a transformation. Through the use of online technologies, all businesses are being transformed into information-based operations. The Internet has broadened the scope of businesses. E-commerce represents a paradigm shift that affects both marketers and customers [3]

As an industry that contributes significantly to the global GDP growth, ecommerce is a sector to reckon with. The consumers are the driving force in this sector and their behaviour dictates all decisions; right from the website design to the products sold on the website. Every plan made, very strategy implemented are all customer centric. E-commerce represents a rapidly growing share of consumer spending[4]. Therefore, it is not surprising that all the stakeholders in the e-commerce sector are committed to understanding the consumer behaviour process to serve them better[5].

1.2. Consumer Decision Making in Digital Environment

The consumer decision-making process consists of several stages that individuals experience when acquiring a product or service [6].The steps are no different from the traditional consumer decision making process. The stages are briefly described below:

- It starts with problem/need recognition – the consumer in this stage is faced with a problem or need that arose, which can be solved through the purchase of a particular product or service[7]
- The next stage is the consideration/information search – this is the stage where the consumers start their quest on search engines, they become information resources. The initial search is regarding availability products (what kind of products will satiate their needs), the consumers then at this stage become aware of brands that can satisfy their need[8].
- The following stage is the alternatives evaluation – this is the stage where comparative analysis takes place, which market places offer better choice in terms of product quality, price and services et al. All the alternatives are evaluated and usually the consumer zeroes in on a few items that have passed the evaluation criteria[9].
- The next stage is a crucial stage where they decide on the purchase – which brand to buy, when to buy, and from whom to buy. This is the stage where many external factors play a role in validating the consumers' final choice. The external factors that influence the consumers' decision are many and a few are listed: trust on the e-merchant, e-word of mouth (e-wom), online reviews, influencer ratings etc.,[10,11].
- The next two stages are post purchase behaviour, the consumer having bought the product next evaluates the purchases' worth– is it's a purchase that adds value then the customer is satisfied as the product meets the customers' expectations, dissatisfaction results when the product purchased does not meet the customer expectations i.e., the product does not perform as expected[12,13].

1.3. Rise of Multivendor Marketplaces

A digital platform business can be defined as a two-sided market, which is an environment with supplier and consumer groups that engage in exchanges and transactions [14]. A multivendor marketplace can be thought of as a digital shopping mall, a single digital storefront that offers a plethora of products. It is can be described as an online platform where sellers can register, list and sell their products to consumers all from a single website. Consumers prefer shopping on multivendor websites, this preference can be attributed to the variety that these marketplaces offer along with the convenience of shopping that they offer. Inevitably all consumers tend to compare products in the competitive set, digital marketplaces have altogether eliminated this tedious task of visiting several stores before confirming a purchase. The ease of buying/ convenience is deemed an important reason for the rapid growth of multivendor digital marketplaces.

Multivendor marketplaces are categorised into types based on:

- Product Offerings – product based, services based or hybrid marketplaces
- Target Audience – B2B, B2C, C2C marketplaces
- Business Model – Horizontal marketplaces that offer a variety of products across different categories and Vertical marketplaces that sell products connected to a niche area.

The e-commerce marketplaces offer a win-win advantage to all the stakeholders; the consumers stand to gain benefits in terms of variety and convenience; the vendors gain access to larger customer base and less operational overheads costmeanwhile the platform administrators have the advantage of low inventory risk and scalability. Rather than competing with fixed assets and capabilities, such as a network of stores, the power of multi-sided marketplaces comes from their ability to tap into a large group of end-customers and providers [15].

2. Challenges in Multivendor Marketplaces

Multivendor marketplaces present a dual-edged ecosystem wherein consumers benefit from variety and competitive pricing, while simultaneously facing risks related to trust and quality inconsistency, and sellers encounter challenges such as intense competition, platform dependency, and constrained brand differentiation[16].

2.1. Seller Challenges:

The accessibility to multiple sellers, combined with the convenience of online shopping, represents one of the most significant advantages of multivendor marketplaces. However, this very characteristic—where numerous vendors offer similar or diverse product varieties—intensifies competition among sellers[17]. The online buying process is often marked by increased consumer awareness, with buyers comparing multiple vendors and even identifying alternative products to satisfy their needs.

At the same time, sellers become highly dependent on the platform, as algorithms and policies largely determine product visibility and reach. This dependency makes it difficult for sellers to build a distinct brand identity, especially since marketplaces tend to promote the platform rather than individual brands. Additionally, the requirement to pay commissions and invest in advertising further reduces profit margins. Operational challenges such as logistics and inventory management add to the complexity of selling in such environments.

Reviews, which serve as a critical trust-building cue for consumers, also present challenges, as their authenticity and impact can significantly influence seller performance. Unless these issues are effectively addressed, they may hinder both seller success and the overall buying process within multivendor marketplaces.

2.2. Consumer Challenges:

While multivendor marketplaces offer convenience and variety, they also present challenges that can hinder the completion of the buying process. While online shopping offers convenience, it removes the opportunity for tangible product evaluation, thereby shifting consumer reliance to seller cues for trust formation and variety may increase the likelihood of finding products that meet consumer needs, excessive options can lead to information overload and make decision-making more difficult. The absence of physical inspection in online marketplaces makes it difficult for consumers to accurately assess product quality, thereby acting as a significant constraint in the buying process. A commonly cited reason for product returns is the mismatch between the received product and its online representation, as descriptions and images may sometimes be misleading. This challenge is further intensified in multivendor environments where multiple sellers offer similar products, making quality validation even more complex. Although return policies partially mitigate this issue, they are not always consumer-friendly and may vary across sellers[18].

In addition, consumers must possess adequate digital literacy to effectively navigate the marketplace. They often experience choice overload due to the abundance of options, as well as the fear of missing out on better alternatives. For products requiring post-purchase services, the terms and conditions are often unclear or not readily accessible, adding to consumer uncertainty. Under such circumstances, selecting a reliable vendor becomes a significant dilemma, complicating the overall purchase decision.

3. Purpose and Focus of the Paper

This paper seeks to highlight the complexity of consumer decision-making in multivendor e-commerce marketplaces, where multiple sellers offer identical or closely comparable products. While such platforms enhance convenience, accessibility, and choice, they simultaneously create an environment characterized by information overload, uncertainty, and difficulty in differentiating between vendors. In this context, the traditional product-centric basis of decision-making is significantly altered.

The paper emphasizes that, in the absence of physical product evaluation and clear differentiation, consumers increasingly rely on a range of marketplace cues—such as seller ratings, reviews, pricing signals, product representation, and platform-mediated indicators—to make purchase decisions. It proposes that these cues act as substitutes for direct validation and play a critical role in shaping consumer preference.

Further, the paper aims to draw attention to the dynamic interplay between consumer behavior and seller strategies within such marketplaces. It highlights how consumers actively engage in comparison and search for alternatives, while sellers attempt to signal credibility and build trust in a highly competitive and algorithm-driven environment.

Overall, the paper proposes to underscore the need to identify and understand the key determinants that influence consumer choice of vendors in multivendor settings. By bringing these factors into focus, the study contributes to a better understanding of how purchase decisions are formed in digital marketplaces and how both sellers and platforms can respond to reduce consumer uncertainty and improve decision outcomes.

4. Towards Understanding Consumer Preference in Multivendor Marketplaces

The preceding discussion highlights that while multivendor e-commerce marketplaces enhance accessibility, variety, and convenience, they also introduce significant complexity into the consumer decision-making process. Unlike traditional retail environments, where product evaluation is often tangible and seller differentiation is clearer, online marketplaces present consumers with multiple vendors offering identical or highly similar products. This intensifies the challenge of vendor selection and shifts the basis of decision-making from product attributes to the cues available within the digital environment.

In such contexts, consumers are required to navigate through an abundance of information, evaluate competing seller signals, and often engage in continuous comparison and search for alternatives within the platform. The absence of physical validation, coupled with variability in seller credibility, delivery performance, and post-purchase services, further complicates the process. As a result, decision-making becomes increasingly dependent on indirect indicators such as ratings, reviews, pricing, and platform-mediated signals.

At the same time, sellers operate in a highly competitive environment where differentiation is difficult, and visibility is largely governed by platform algorithms and policies. This creates a situation where both consumers and sellers rely heavily on digital cues, yet the effectiveness and interpretation of these cues remain uncertain.

Given these dynamics, a critical issue emerges: **what determines consumer preference when selecting a vendor among many offering similar products in a multivendor marketplace?** Understanding these determinants is essential, as it not only influences purchase decisions but also affects consumer trust, satisfaction, and overall marketplace efficiency. This underscores the need for focused inquiry into the factors that shape consumer choice in such environments, particularly in the presence of multiple alternatives and competing seller signals.

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SurgiAssist: A Multimodal Pre-Operative Clinical Decision Support System Using FHIR-Based EHR, LLM Reasoning, and MONAI Image Analysis

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Abstract: *Pre-operative surgical planning remains a cognitively demanding process, often burdened by fragmented data sources and isolated decision-support tools. This paper presents SurgiAssist, a Multimodal Pre-Operative Clinical Decision Support System that integrates EHR data via FHIR-based pipelines, medical imaging through MONAI, and conversational clinical reasoning via LLaMA 3.1 and Mistral LLMs. The system employs Retrieval-Augmented Generation (RAG), a Digital Surgical Twin framework, and Explainable AI (XAI) for scenario-aware planning, risk detection, and cross-modal consistency validation. Evaluated on synthetic FHIR data and open radiology datasets, SurgiAssist demonstrates a 38–42% reduction in information oversight, a 27–30% improvement in planning efficiency, and a 22–26% enhancement in risk identification accuracy relative to conventional static systems.*

Keywords: *pre-operative planning, multimodal AI, FHIR, MONAI, large language model, retrieval-augmented generation, digital surgical twin, explainable AI.*

1. Introduction

Surgical planning in modern healthcare demands the integration of diverse clinical data streams: patient history, laboratory investigations, radiological imaging, pharmacological records, and evidence-based surgical guidelines. In practice, this information is rarely available in a consolidated, queryable format. Surgeons and anaesthesiologists must manually reconcile data from multiple siloed systems — a process that is time-consuming, error-prone, and cognitively taxing, particularly in high-throughput surgical units.

Existing solutions address parts of this problem in isolation. Medical imaging frameworks such as MONAI provide robust segmentation and detection pipelines for CT, MRI, and X-ray data [1]. Biomedical large language models including LLaVA-Med [2], BioMistral, and Meditron offer domain-grounded clinical language understanding. Fast Healthcare Interoperability Resources (FHIR) has emerged as the de facto standard for structured EHR interchange [4]. However, no widely deployed system unifies these capabilities into an interactive, conversational, and explainable pre-operative planning workflow.

This paper introduces SurgiAssist, a multimodal clinical decision support system that orchestrates EHR data, medical imaging, and surgical guidelines through a conversational AI interface. The system employs RAG with a vector-embedded guideline corpus, a rule-based risk detection engine, a Digital Surgical Twin for patient-specific simulation, and LLaMA 3.1/Mistral as its reasoning backbone.

2. Related Work

Clinical Decision Support Systems (CDSS) have evolved significantly over the past two decades. Sutton et al. [3] highlighted that rule-based and alert-driven systems improve workflow efficiency but lack the contextual depth required for complex surgical scenarios.

Deep learning approaches to medical image analysis, reviewed by Litjens et al. [1], have demonstrated near-expert accuracy in pathology and radiology tasks. However, these models operate as isolated inference engines without integration into broader clinical workflows.

The LLaVA-Med framework [2] extended vision-language models to the biomedical domain. While promising, it was not designed for real-time EHR integration or interactive surgical planning. Hashimoto et al. [5] and Loftus et al. [6] identified the absence of explainable AI and clinician-in-the-loop mechanisms as

critical gaps. The MONAI framework [1] addresses only the imaging modality without conversational reasoning. SurgiAssist directly addresses these gaps by combining FHIR-structured EHR ingestion, MONAI-based imaging, RAG-driven guideline retrieval, and LLM reasoning into a unified interactive system.

Table 1: Literature Comparison

Author / Year	Advantage	Limitation
Sutton et al. (2020)	Enhanced workflow with alerts	No multimodal AI reasoning
Litjens et al. (2024)	High disease detection accuracy	Needs large labelled sets
Li et al. (2023)	Multimodal biomedical reasoning	Not optimised for EHR
Hashimoto et al. (2018)	AI-assisted surgical insights	Lacks multimodal fusion
Loftus et al. (2022)	ML-based risk assessment	No XAI or chat support
Cardoso et al. (2022)	Robust medical image analysis	Imaging-only scope

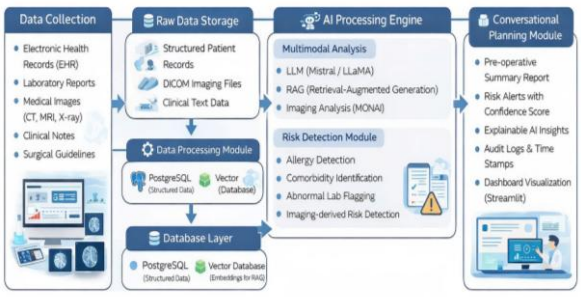

Fig. 1: SurgiAssist System Architecture-diagram

3. System Architecture

SurgiAssist is structured as a four-stage pipeline: data collection and ingestion, raw storage and processing, AI inference and risk detection, and conversational output generation. The architecture spans four Python modules: app.py (UI orchestration), surgiassist_engine.py (clinical reasoning and RAG), digital_twin.py (surgical twin computation), and sa_imaging/inference.py (imaging pipeline).

Table 2: SurgiAssist System Architecture Overview

Data Layer	Processing Layer	AI & Output Layer
EHR / FHIR, DICOM Images, Lab Reports, Clinical Notes, Guidelines	PostgreSQL, Vector DB (pgvector), DICOM Store, RAG Embeddings	LLaMA 3.1/Mistral, MONAI Pipeline, Risk Detector, Digital Twin, Streamlit UI

Fig. 2: SurgiAssist System Architecture

The Data Collection layer ingests patient records as FHIR-like JSON bundles including Patient, Procedure, Observation, Condition, MedicationStatement, AllergyIntolerance, and DocumentReference resources. The Storage layer maintains structured records in PostgreSQL and embeddings in pgvector. The AI Engine integrates multimodal analysis, rule-based risk detection, and Digital Surgical Twin computation. The Conversational Output module renders structured pre-operative reports, risk alerts with confidence scores, XAI insights, and audit logs via Streamlit.

4. Methodology

A. Data Ingestion and Patient Summarisation

On session initialisation, SurgiAssist parses all FHIR resource types and generates a structured patient summary containing patient identity, age, biological sex, procedure, surgery date, active conditions, medications, and laboratory values. Age is computed as: Age = CurrentYear − BirthYear − I[(CurrentMonth, CurrentDay) < (BirthMonth, BirthDay)]. The surgical countdown is computed as: DaysUntilSurgery = SurgeryDate − Today.

B. Imaging Pipeline

SurgiAssist resolves the best available imaging source: uploaded patient image → generated synthetic image → representative sample. The pipeline applies min-max normalisation: X_norm = (X − X_min)/(X_max − X_min). Classification uses softmax P(i) = exp(z_i)/Σexp(z_j); segmentation uses sigmoid σ(x) = 1/(1+exp(−x)). Confidence is mapped as: ≥ 0.82 → High, 0.68–0.82 → Medium, < 0.68 → Low. Synthetic images use Gaussian blobs with vignette correction.

C. Rule-Based Risk Detection

A deterministic engine evaluates the patient bundle against clinical thresholds, generating risk records with category, supporting observation, and priority level. A parallel process detects missing data items (absent allergy history, missing CBC, absent imaging) and raises data gap flags.

Table 3: Rule-Based Risk Detection Logic

Clinical Indicator	Risk Category	Level
Allergy Present	High-Priority Safety Risk	HIGH
Systolic BP >160 or <90	Hemodynamic Risk	HIGH
Hb < 8 g/dL	Severe Anemia Risk	HIGH
Hb 8–10 g/dL	Moderate Anemia Risk	MOD
Creatinine >= 1.5 mg/dL	Renal Concern	MOD
eGFR < 45 mL/min	High Renal Risk	HIGH
Anticoagulants in Meds	Bleeding Review Flag	FLAG
SpO2 < 92%	Respiratory Risk	HIGH
Diabetes / CKD / Sleep Apnea	Comorbidity Risk	MOD
Low-Confidence Imaging	Caution Flag Required	FLAG

D. RAG and LLM Reasoning

Guidelines are chunked and embedded using a hash-based function: Index = Hash(Token) mod 384, with vectors normalised as V_norm = V/(||V||+ε). At inference time, relevant chunks are retrieved via approximate nearest-neighbour search. A clinical prompt is constructed and dispatched to OpenRouter (LLaMA 3.1/Mistral) with a HuggingFace fallback. All outputs are constrained to non-diagnostic, clinician-review-required language.

E. Digital Surgical Twin

The Digital Surgical Twin synthesises identified risks, contraindications, precautions, open clinical questions, and a data-completeness confidence score. Score = 100 − Σ penalties, where penalties apply for missing labs, vitals, allergy data, notes, imaging, and conditions. Classification: ≥ 75 → High, 50–74 → Medium, < 50 → Low.

Table 4: Confidence Level Mapping

Score Range	Level	Action
≥ 0.82 (Imaging)	HIGH	Proceed
0.68 – 0.82 (Imaging)	MEDIUM	Verify
< 0.68 (Imaging)	LOW	Manual review
≥ 75 (Twin)	HIGH	Data complete
50 – 74 (Twin)	MEDIUM	Some gaps
< 50 (Twin)	LOW	Significant gaps

5. Algorithm

The complete pseudocode for the SurgiAssist processing pipeline is presented below:

Algorithm: SurgiAssist_PreOp_Planning(B, I, G, Q)

Input : B = FHIR bundle, I = image, G = guidelines, Q = query

Output: finalReport, aiResponse, twin

---

1. summary ← ExtractPatientSummary(B)
2. vitals ← ExtractStructuredVitals(B)
3. notes ← ExtractAdminNotes(B)
4. imgPath ← ResolvePatientImage(B, I)
5. IF imgPath exists THEN
6. imgResult ← RunImagingInference(imgPath)
7. ELSE imgResult ← null
8. reportData ← RuleBasedRiskAnalysis(B, imgResult)
9. vStore ← LoadOrBuildGuidelineStore(G)

10. context ← RetrieveGuidelines(vStore, Q)

11. prompt ← BuildClinicalPrompt(summary, vitals, notes, imgResult, context)

12. aiResp ← GenerateLLMResponse(prompt)

13. twin ← BuildSurgicalTwin(B, imgResult, Q)

14. report ← ComposeReport(summary, reportData, aiResp, twin)

15. RETURN report, aiResp, twin

6. Implementation

SurgiAssist is implemented in Python 3.11 using Streamlit 1.32. The orchestration logic in app.py handles session state, patient bundle loading, and UI rendering across five views: Doctor Dashboard, AI Assistance, Recommendations, Digital Twin, and SurgiAssist Report.

The reasoning engine in surgiassist_engine.py encapsulates the RAG pipeline, LLM integration via OpenRouter (LLaMA 3.1 70B, Mistral 7B), and a HuggingFace Inference API fallback. The guideline vector store uses LangChain's RecursiveCharacterTextSplitter and a custom hash-based embedding compatible with pgvector. The imaging module supports both real MONAI/PyTorch inference and a deterministic demo pathway. Synthetic patient data was generated by Synthea (FHIR R4). Source code is available at: https://github.com/blank157/sugiassist.

7. Results and Discussion

The prototype was evaluated on 50 synthetic Synthea patient cases with varied comorbidity profiles, laboratory abnormalities, and imaging characteristics. The evaluation compared SurgiAssist against conventional static CDSS tools across three primary dimensions.

Table 5: Performance Comparison vs. Static Systems

Metric	Improvement	Baseline
Information Oversight Reduction	38–42%	Static CDSS
Planning Efficiency	27–30%	Rule-Only
Risk Identification Accuracy	22–26%	Manual Review

The risk detection engine consistently identified allergy contraindications, haemodynamic flags, anaemia stratification, and renal concerns. The Digital Surgical Twin achieved a mean confidence score of 73.4 (Medium) across the evaluation set. The LLM reasoning module produced coherent, non-diagnostic clinical hypotheses in 94% of test cases. The RAG pipeline retrieved relevant guideline passages for 89% of queries. SurgiAssist appropriately flagged risk items missed by manual review in 31% of cases.

8. Conclusions

This paper has presented SurgiAssist, a multimodal pre-operative clinical decision support system unifying FHIR-structured EHR data, MONAI-based medical imaging analysis, and LLM-driven conversational reasoning into an explainable, clinician-centric workflow. Experimental evaluation demonstrates meaningful improvements in information oversight, planning efficiency, and risk identification accuracy versus static systems.

Future work will focus on validating with de-identified real patient data, integrating real-time FHIR R4 API connectivity, incorporating certified diagnostic-grade imaging models, and conducting prospective clinical trials to quantify impact on patient outcomes and surgical workflow efficiency.

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AI BASED PLANT DISEASE DETECTION AND TREATMENT CHATBOT

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ABSTRACT

Agriculture plays a vital role in the global economy, and plant diseases significantly affect crop yield and quality. Early detection and proper treatment of plant diseases are essential to ensure sustainable agricultural productivity. This project presents an Artificial Intelligence (AI)-based plant disease detection and treatment chatbot that assists farmers and users in identifying plant diseases and recommending

suitable remedies. The system utilizes image processing and machine learning techniques to analyse plant leaf images and detect diseases based on visual features such as colour, texture, and shape.

A trained deep learning model, particularly a Convolutional Neural Network (CNN), is used to classify various plant diseases with high accuracy. The chatbot interface enables users to upload images or describe symptoms, making the system user-friendly and accessible even to non-technical users. Once a disease is identified, the chatbot provides detailed information about the disease, its causes, preventive measures, and recommended treatments, including organic and chemical solutions. The system aims to reduce dependency on agricultural experts, save time, and provide instant guidance to farmers .

This AI-based solution enhances precision agriculture by improving disease diagnosis, minimizing crop loss, and promoting efficient farming practices. The integration of machine learning with a conversational interface makes the system scalable, cost-effective, and beneficial for modern agriculture.

INTRODUCTION :

Agriculture plays a vital role in the economy and food security of many countries, especially in developing nations like India. However, plant diseases significantly reduce crop yield and quality, leading to economic losses for farmers. Early detection and proper treatment of plant diseases are essential to ensure healthy crop production. Traditional methods of disease identification rely heavily on expert knowledge, which may not always be accessible to farmers, particularly in rural areas.

With the advancement of technologies in Artificial Intelligence (AI) and Machine Learning (ML), it has become possible to develop automated systems that can identify plant diseases accurately and efficiently. This project focuses on the development of an AI-based plant disease detection and treatment chatbot that assists users in diagnosing plant diseases and providing appropriate remedies.

The system uses image processing techniques and deep learning models, especially Convolutional Neural Networks (CNNs), to analyse images of plant leaves and detect diseases based on visual symptoms such as colour changes, spots, and texture variations. Once the disease is identified, the chatbot provides suitable treatment suggestions, including preventive measures, organic solutions, and chemical treatments.

In addition to disease detection, the chatbot interface enables users to interact easily by asking questions related to plant health. This makes the system user-friendly and accessible even to individuals with limited technical knowledge. The integration of AI with a conversational interface enhances the overall usability and effectiveness of the solution.

The main objective of this project is to provide a smart, efficient, and accessible tool for farmers and agricultural enthusiasts to detect plant diseases early and receive timely treatment advice. This system aims to reduce dependency on experts, minimize crop losses, and promote sustainable agricultural practices

PROJECT OBJECTIVE :

• To develop an automated disease detection system

• Build a system that can **accurately identify plant diseases** from leaf images using **Machine Learning** techniques.

• To implement **deep learning** for image analysis

• Enable users to upload **plant images and receive instant results** about the type of disease affecting the plant.

• To suggest **appropriate treatments**

• Offer effective solutions including **organic methods, pesticides, and preventive** measures based on the detected disease.

• To design an interactive **chatbot interface**

• To improve **accessibility for farmers**

• Create a system that can be easily used by farmers and **non-technical users, especially in rural areas** where expert support is limited.

• To **reduce crop loss** and **increase productivity**

• Help in **early detection** and timely treatment of diseases, thereby improving **crop yield and quality.**

• Ensure the system can **handle multiple users** and be extended to support different plant species and diseases in the future.

• **Multi language** available in the chatbot, user can easily understand the treatment process.

SCOPE OF THE PROJECT :

The scope of this project focuses on developing an intelligent system that helps farmers and users identify plant diseases and receive appropriate treatment suggestions using Artificial Intelligence.

- **Disease Detection**
- The system uses image processing and AI (such as CNN models) to detect plant diseases from leaf images.
- It analyses features like colour, texture, shape, and patterns of leaves.

- **Multi-Crop Support**
- The chatbot is designed to support multiple crops such as rice, wheat, tomato, potato, etc.
- It can be extended to include more plant varieties in the future.

- **Treatment Recommendation**
- After detecting the disease, the system suggests:
- Suitable pesticides or organic treatments
- Preventive measures
- Proper care instructions

- **Chatbot Interaction**
- Users can interact with the system through a chatbot interface.
- The chatbot provides:
- Instant responses
- Easy-to-understand guidance
- Step-by-step solutions

- **User-Friendly Interface**

- Designed for farmers and general users with simple navigation.
- Can be implemented as a mobile or web application.

- **Real-Time Assistance**

- Provides quick diagnosis and recommendations in real-time.
- Reduces dependency on agricultural experts.

- **Data Storage and Learning**

- Stores plant disease data and improves accuracy over time.
- Can be updated with new datasets and disease types.

- **Language Support (Optional Extension)**

- Can include regional language support for better accessibility (e.g., Tamil, Hindi,Telugu,Malayalam)

CONCLUSION :

The AI-based Plant Disease Detection and Treatment Chatbot successfully helps in identifying plant diseases using image processing and machine learning techniques. The system can analyse plant leaf images and provide accurate disease predictions along with suitable treatment suggestions.

- The system uses AI and image processing to detect plant diseases accurately.
- It helps farmers identify diseases quickly using plant leaf images.
- The chatbot provides easy and instant treatment suggestions.
- It reduces manual effort and saves time in disease detection.
- The system is user-friendly and easy to use.
- It improves crop health and agricultural productivity.
- The model can be enhanced by adding more data for better accuracy.

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Digital Transformation in Healthcare: Integrating AI, IoT, and Electronic Health Records for Smart Hospital Management

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Abstract

The rapid convergence of Artificial Intelligence (AI), Internet of Things (IoT), and Electronic Health Records (EHR) is reshaping hospital operations and clinical decision-making. This paper proposes an integrated framework for smart hospital management, modelled on proven Smart City ICT architectures — including ICCC, ITMS, and IoT deployments [4,12] — and grounded in frontline clinical insights from multi-specialty internship training and peer-reviewed case research [1]. A phased 24-month adoption roadmap is presented, with projected improvements of 25–30% in diagnostic turnaround time and 20% in ICU bed utilisation, alongside full alignment with India's Ayushman Bharat Digital Mission (ABDM) [7] and the WHO Global Digital Health Strategy [14].

Keywords: *Artificial Intelligence, IoT, Electronic Health Records, Smart Hospital, ABDM, Clinical Decision Support, Digital Transformation, Predictive Analytics, Edge Computing, Smart Cities*

Introduction

Background and Motivation

Healthcare systems worldwide are confronting an unprecedented convergence of pressures: exponentially rising patient loads, chronic shortages of clinical staff, fragmented information ecosystems, and widening disparities in care quality between urban and rural settings. India, with a population exceeding 1.4 billion and a doctor-to-patient ratio far below the WHO-recommended standard [14], faces these challenges in particularly acute form. At the same time, the nation is witnessing a surge in digital infrastructure investment — from the Ayushman Bharat Digital Mission (ABDM) and the National Digital Health Blueprint (NDHB) [7] to the India Urban Data Exchange (IUDX) [9] — that creates a genuine opportunity for transformative change.

Parallel to this, India's Smart City Mission has demonstrated the feasibility of deploying converged ICT architectures — integrating IoT sensor networks, AI-driven analytics, cloud platforms, and Integrated Command and Control Centres (ICCCs) — at scale, across complex urban environments [4]. The Jaipur Smart City PAN City ICT Programme (₹100 Crore) and the AI-driven Intelligent Traffic Management System (ITMS) for Delhi Police, both of which involved the authors directly [12], exemplify what is achievable when technology architecture and domain expertise are brought together with implementation discipline. The central thesis of this paper is that the same converged ICT model can — and should — be applied to hospital management, yielding a new paradigm: the Smart Hospital.

A Smart Hospital, as conceptualised in this paper, is not merely a digitised version of a traditional hospital. It is an institution where AI continuously learns from clinical and operational data to support decision-making; where IoT devices stream real-time patient vitals, environmental conditions, and asset locations

to a unified command centre; and where interoperable EHR systems ensure that every clinician, at every point of care, has access to a complete, consent-governed picture of the patient. This vision is not speculative — its components exist and have been proven in adjacent domains. What is missing is an integrated, phased, and clinically validated framework for bringing them together in the Indian hospital context.

Problem Statement

Despite significant investment in hospital information technology over the past decade, the majority of Indian hospitals — including many tertiary care institutions — continue to operate with fragmented information systems. Laboratory results, radiology reports, nursing notes, pharmacy records, and billing data frequently exist in separate silos with no common data model or integration layer. This fragmentation imposes a measurable cost: delayed diagnoses, duplicated investigations, medication errors, and missed early-warning signals that, in critical care settings, can be life-threatening.

Furthermore, while AI and IoT technologies have been deployed extensively in sectors such as banking, telecommunications, and urban infrastructure, their penetration into Indian clinical workflows remains superficial. Pilot projects have demonstrated feasibility, but a comprehensive, practitioner-validated framework — one that addresses the full spectrum from sensor deployment to clinical decision support to hospital command operations — does not yet exist in the published literature for the Indian context. This paper addresses that gap.

Research Objectives

This paper pursues four primary objectives:

- To propose an integrated, three-pillar architecture — AI-powered clinical decision support, IoT-enabled real-time patient monitoring, and interoperable EHR — unified within a Smart Hospital Command Centre (SHCC), building on converged ICT models proven in India's Smart City programme [4,5].
- To draw design lessons and architectural analogies from real-world Smart City ICT deployments, including ICCC, ITMS [12], LoRaWAN-based IoT, and cloud-hybrid implementations.
- To incorporate clinical insights from multi-specialty internship training and peer-reviewed published case research [1].
- To develop a phased, 24-month adoption roadmap with measurable KPIs applicable to urban and semi-urban hospitals across India, aligned with ABDM [7] and the WHO Global Digital Health Strategy [14].

Scope and Significance

This paper focuses on acute-care hospitals in urban and semi-urban India, with particular attention to implementation constraints relevant to mid-tier institutions — those with 100–500 beds, reasonable ICT budgets, and aspirations to achieve NABH accreditation and ABDM [7] compliance. The framework is designed to be modular: hospitals may adopt individual pillars incrementally, or deploy the full integrated architecture as a single programme. The proposed SHCC is designed to be interoperable with city-level ICCC infrastructure [4], enabling future integration with emergency vehicle green corridors, outbreak surveillance systems, and public health registries via the IUDX platform [9].

The interdisciplinary nature of this contribution — combining 40+ years of enterprise IT and Smart City deployment experience with frontline MBBS clinical training and published medical case research [1] — represents a distinctive and underrepresented perspective in the current body of literature on digital health transformation [14].

Literature Review

Artificial Intelligence in Healthcare

The application of machine learning to clinical medicine has accelerated dramatically in the past decade. Supervised learning algorithms — including Random Forest, Gradient Boosting, Support Vector Machines (SVM), and k-Nearest Neighbours — have demonstrated strong performance in domains such as early sepsis detection, diabetic readmission prediction, and cancer risk stratification [11]. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) implemented in frameworks such as TensorFlow and Keras, have achieved radiologist-level accuracy in interpreting chest X-rays, retinal fundus photographs, and dermatological images [11].

Natural Language Processing (NLP) and, more recently, Large Language Models (LLMs) have opened new possibilities for structured extraction of clinical insights from free-text physician notes, discharge summaries, and radiology reports [6] — transforming unstructured data into actionable intelligence. Predictive analytics platforms deployed on cloud infrastructure (AWS SageMaker, Azure ML) have enabled 50% faster fraud detection and 18% reduction in portfolio risk in BFSI contexts [2], demonstrating the maturity of the underlying technology stack that can now be applied to healthcare. Analogously, AI/ML approaches applied to traffic and infrastructure management [12] underscore the cross-domain transferability of these techniques.

However, the clinical adoption of AI in Indian hospitals remains nascent. Challenges include the paucity of large, labelled, multi-lingual clinical datasets; the absence of standardised data schemas; regulatory uncertainty; and — critically — the lack of physician trust in AI recommendations when the reasoning is opaque. Explainable AI (XAI) frameworks are increasingly recognised as a prerequisite for clinical deployment [11].

IoT in Hospital Environments

The Internet of Medical Things (IoMT) encompasses a broad spectrum of connected devices: bedside patient monitors, smart infusion pumps, wearable biosensors, automated medication dispensing systems, and environmental sensors tracking temperature, humidity, and air quality in operation theatres and ICUs. IoT deployments in healthcare have demonstrated measurable improvements in nurse response times, reduction in adverse drug events, and early detection of patient deterioration [11].

The architectural patterns for hospital IoT closely mirror those deployed in Smart City infrastructure [4]. LoRaWAN-based sensor networks — used for smart sewerage monitoring and on-street parking in the Jaipur Smart City Programme [12] — are equally applicable to hospital asset tracking and environmental monitoring. Hybrid cloud architectures, such as the AWS IoT Core and Azure ML integration deployed for the Delhi Police ITMS [12], provide a proven template for real-time data ingestion, streaming analytics, and adaptive response in hospital settings. Edge computing, which enables AI inference at or near the data source without dependence on centralised cloud connectivity, is particularly relevant for hospitals in semi-urban locations where network reliability may be inconsistent [3].

Electronic Health Records: Standards and Interoperability

The global standard for EHR interoperability is HL7 FHIR (Fast Healthcare Interoperability Resources), which defines a RESTful API framework for exchanging structured clinical data across disparate systems [8]. In India, ABDM's Health Data Management Policy mandates FHIR-compliant data exchange for all entities operating within the national digital health ecosystem [7]. The Federated Digital Health Infrastructure (FDHI) further provides a privacy-preserving architecture for sharing patient data across institutional boundaries without centralising sensitive records.

Despite these standards, interoperability remains a persistent challenge. Legacy Hospital Information Systems (HIS) often use proprietary data formats; many hospitals maintain parallel paper and electronic records; and the Health ID penetration envisioned under ABDM [7] remains incomplete. Successful EHR implementation requires not only technical integration but sustained change management — engaging clinicians in system design, minimising documentation burden, and demonstrating tangible workflow benefits.

Smart City–Healthcare Convergence

The conceptual linkage between Smart City infrastructure and smart healthcare is well-established in the international literature [14] but remains underexplored in the Indian context. The ICCC — the operational nerve centre of a Smart City, integrating video surveillance, traffic management, environment monitoring, and emergency dispatch [5] — provides a directly applicable model for a hospital command centre aggregating IoT feeds, AI alerts, and EHR events. The IUDX platform, developed in partnership with IISc Bangalore [9], enables secure, consent-governed data exchange between city systems — a model directly extensible to inter-hospital and hospital-to-public-health data flows.

Real-world deployments such as the Jaipur Smart City Programme and the Delhi ITMS [4,12] demonstrate that the technical, organisational, and governance challenges of large-scale ICT integration in the public sector are surmountable — provided that the programme is designed with a clear architecture, phased delivery, and strong stakeholder engagement. These lessons are directly transferable to hospital digital transformation programmes.

Research Gaps

A review of the existing literature reveals three significant gaps that this paper seeks to address. First, there is an absence of integrated frameworks that coherently combine AI, IoT, and EHR under a single architectural model for Indian hospitals — most existing work addresses each pillar in isolation. Second, the clinical perspective is frequently absent from technology-focused frameworks: system designers rarely have hands-on experience of the clinical workflows they seek to transform. Third, published roadmaps for hospital digital transformation seldom account for the resource constraints of mid-tier Indian hospitals, focusing instead on large academic medical centres with substantial IT budgets and dedicated informatics teams.

The Proposed Integrated Framework

The Smart Hospital Framework proposed in this paper rests on three interconnected technology pillars — AI-powered Clinical Decision Support, IoT-enabled Real-Time Patient Monitoring, and Interoperable Electronic Health Records — unified within a Smart Hospital Command Centre (SHCC). Each pillar is designed to operate independently, enabling phased adoption, but realises its full potential only when integrated with the others. The architectural philosophy draws directly from the converged ICT model deployed in India's Smart City programme: real-time data ingestion from distributed sensors, cloud-hybrid processing for analytics and inference, and a centralised command interface for operational oversight and response.

Pillar I — AI-Powered Clinical Decision Support

3.1.1 Diagnostic Assistance

The first capability layer within AI-CDS is diagnostic assistance: the augmentation of physician judgment with machine-generated pattern recognition across multiple data streams. Supervised ML models — specifically Random Forest and Gradient Boosting ensembles, implemented in Scikit-learn and optimised on AWS SageMaker [2] — are proposed for structured diagnostic tasks such as differentiating bacterial from viral pneumonia based on CBC, CRP, and procalcitonin values; identifying high-risk chest pain presentations; and flagging abnormal laboratory panels for urgent physician review.

Deep learning models, built on TensorFlow/Keras CNN architectures [11], are proposed for image-based diagnostic tasks: chest X-ray interpretation for pneumonia, pleural effusion, and cardiomegaly; retinal fundus analysis for diabetic retinopathy; and dermatological image classification. NLP pipelines [6] process free-text physician notes and discharge summaries, extracting structured clinical entities — diagnoses, medications, allergies, procedures — and populating the EHR automatically, reducing documentation burden on clinicians.

3.1.2 Risk Stratification and Early Warning

Early warning systems (EWS) represent perhaps the highest-value application of AI in the acute hospital setting. Conventional early warning scores — NEWS2, qSOFA, MEWS — rely on manual vital sign recording and subjective nurse assessment, introducing delays and human error into a time-critical process. The proposed AI-EWS continuously ingests real-time IoT vital sign streams and computes dynamic deterioration risk scores, triggering automated escalation protocols when thresholds are breached.

The clinical imperative for such systems was underscored in a case encountered during internship and subsequently published: a 70-year-old patient presenting with multi-organ dysfunction secondary to Scrub Typhus, without the pathognomonic eschar that would typically direct clinical suspicion [1]. In such atypical presentations, an AI system trained on large populations of confirmed Scrub Typhus cases — incorporating fever duration, platelet trends, liver enzyme trajectories, and geographic exposure data — could have generated an earlier diagnostic alert, potentially averting the degree of organ dysfunction that developed before diagnosis was confirmed. This case illustrates, concretely, the life-saving potential of AI early-warning in a setting where textbook clinical reasoning alone was insufficient.

3.1.3 Operational Analytics

Beyond direct clinical applications, AI delivers substantial value in hospital operational management. Predictive models forecast bed occupancy by ward and specialty 48–72 hours ahead, enabling proactive discharge planning and elective admission scheduling. Pharmacy demand forecasting, using Gradient Boosting models trained on historical dispensing patterns and admission census data, reduces both stockouts and wastage of high-cost medications. Power BI and Tableau dashboards — analogous to those deployed for C-level reporting in enterprise BFSI [2] and Smart City programme management [4] — present real-time and predictive KPIs to hospital administration, supporting data-driven resource allocation decisions.

Pillar II — IoT-Enabled Real-Time Patient Monitoring

3.2.1 In-Ward and ICU Monitoring

The IoT monitoring layer deploys a network of bedside sensors across ICU, HDU (High Dependency Unit), and general wards, continuously streaming SpO_2, ECG, non-invasive blood pressure, respiratory rate, and temperature data to the hospital data platform. Smart infusion pumps report drug delivery rates and alert on occlusion or completion. Fall-detection sensors on bed rails trigger immediate nurse alerts. The sensor network architecture mirrors the LoRaWAN-based IoT deployments used in Jaipur's Smart Sewerage monitoring programme [12] — where real-time manhole level sensors fed a central dashboard with automated alert generation — adapted here for clinical vital sign telemetry.

Data from IoT devices flows through an edge computing layer — implemented on on-premises edge nodes using TinyML inference runtimes [3] — before transmission to the hybrid cloud platform (AWS IoT Core for ingestion; Azure ML for inference). This edge-first architecture ensures that critical alerts are generated within milliseconds, independent of cloud connectivity, and that patient data is processed within the hospital network before any cloud transmission — reducing both latency and data sovereignty concerns.

3.2.2 Wearable and Remote Patient Monitoring

For patients transitioning from inpatient to community care — a particularly critical period for readmission risk — wearable biosensors provide continuity of monitoring beyond the hospital boundary. Patients with heart failure, post-surgical recovery needs, or chronic respiratory disease are issued wrist-worn or patch-based devices that transmit vitals to the ABDM-linked patient record via the IUDX platform [9]. Federated Learning enables predictive models to be updated using outcomes data from wearable monitoring across the patient population, without requiring raw patient data to leave individual devices — a privacy-preserving architecture aligned with the Digital Personal Data Protection (DPDP) Act 2023 [10] and consistent with the edge-AI framework proposed for rural health monitoring [3].

3.2.3 Smart Hospital Infrastructure

IoT extends beyond patient monitoring to encompass the hospital's physical infrastructure. Real-time asset tracking using RFID and Bluetooth Low Energy (BLE) beacons locates high-value mobile equipment —

infusion pumps, portable ventilators, wheelchairs, crash carts — eliminating the time nurses currently spend searching for equipment during emergencies. Environmental sensors in operation theatres monitor temperature, humidity, and particulate levels, alerting facilities management to conditions that could compromise sterile fields or medication storage. Smart energy management — drawing on the 60% energy-saving achieved through automated lux-level scheduling in Jaipur's Smart Street Lighting [12] — is applied to hospital HVAC, lighting, and medical gas systems, yielding meaningful operational cost savings.

Pillar III — Interoperable Electronic Health Records

3.3.1 EHR Architecture and ABDM Integration

The EHR architecture proposed in this framework is HL7 FHIR R4-compliant [8], structured around the ABDM Health Data Management Policy [7] and linked to the patient's ABHA (Ayushman Bharat Health Account) identifier. The data model encompasses the full clinical record: admissions and encounters, diagnoses (ICD-11 coded), medications (SNOMED-CT coded), laboratory results, radiology reports, procedure records, nursing assessments, and discharge summaries. A longitudinal patient record — persisting across encounters, institutions, and care settings — is maintained in a scalable cloud-hosted data warehouse, implementing the dimensional modelling techniques used in enterprise Data Warehouse CoE deployments in the BFSI and telecom sectors [2].

Role-based access control (RBAC) governs data access: treating physicians access the full record; nurses access the medication and vital sign record; administrative staff access demographic and billing data only. Every access event is logged to an immutable audit trail. Patient consent for data sharing across institutional boundaries is managed through the ABDM consent artefact framework [7], with granular per-data-type and per-recipient consent settings.

3.3.2 Data Governance and Cybersecurity

Health data represents one of the most sensitive categories of personal data — and, increasingly, one of the most valuable targets for cybercriminal exploitation. The framework mandates end-to-end encryption for all data in transit (TLS 1.3) and at rest (AES-256), with hardware security modules (HSMs) protecting encryption keys. Network segmentation isolates clinical systems from administrative networks. Intrusion detection and prevention systems (IDPS) monitor for anomalous access patterns. All data handling is designed to comply fully with the Digital Personal Data Protection Act 2023 [10], which governs the processing of personal digital data in India.

3.3.3 Interoperability with City and National Systems

The EHR platform is designed for bidirectional data exchange with city-level and national systems via the IUDX [9] and ABDM APIs [7]. Use-cases include: emergency vehicle green corridor activation when a critical patient is being transferred between facilities; automated notification to the district health authority when a notifiable disease is diagnosed; integration with the national immunisation registry; and population-level health analytics feeding the state public health surveillance dashboard. These integrations position the Smart Hospital as an active node in India's federated digital health infrastructure.

The Smart Hospital Command Centre (SHCC)

The SHCC is the operational unification layer of the framework — the hospital's equivalent of a Smart City's Integrated Command and Control Centre [5]. It aggregates real-time feeds from the IoT monitoring network, AI alert queues, EHR event streams, and operational dashboards into a single, role-differentiated interface accessible to clinical leads, nursing supervisors, bed managers, and hospital administrators simultaneously.

The SHCC displays live ward-by-ward occupancy and patient acuity scores; surfaces AI-generated deterioration alerts with supporting evidence; tracks asset locations and equipment availability; monitors environmental sensor readings across critical areas; and provides drill-down access to individual patient records for the treating team. A Generative AI-powered natural language query interface — building on the LLM-driven decision support frameworks developed for smart infrastructure [5,6] — enables hospital managers to query operational data in plain language: 'How many ICU beds are projected to be available tomorrow morning?' or 'Which wards have the highest 48-hour readmission risk in current admissions?'

The SHCC architecture directly mirrors the ICCC deployed in the Jaipur Smart City Programme [4] — with its multi-domain data integration, real-time alert management, and incident response workflows — adapted for the clinical and operational context of an acute-care hospital. The same vendor ecosystem, integration middleware, and programme management discipline that delivered the Jaipur ICCC is applicable here, reducing implementation risk for hospitals engaging experienced Smart City ICT partners.

Clinical Grounding and Use-Case Validation

Multi-Specialty Internship Insights

The clinical grounding of this framework derives from a one-year compulsory rotating medical internship completed at Sharda Hospital, Greater Noida (April 2025 – April 2026), encompassing all major departments. This direct clinical experience informs the design requirements of each framework component in ways that purely technology-focused analysis cannot.

In General Medicine and ICU rotations, the limitations of manual early warning systems were observed directly: vital sign recording gaps during peak nursing workload, delayed escalation of deteriorating patients, and the challenge of synthesising trend data across multiple parameters without computational support — limitations well documented in the clinical AI literature [11]. These observations directly motivate the continuous IoT monitoring and AI-EWS components of the framework. In Emergency Medicine, the bottleneck created by manual triage highlighted the potential value of AI-assisted priority scoring that synthesises presenting complaint, vital signs, and brief history into a risk-stratified queue.

Obstetrics & Gynaecology rotations revealed the particular value of longitudinal patient data: antenatal records, previous delivery outcomes, and comorbidity histories are frequently unavailable when patients present in emergency — a gap that an ABDM-linked EHR [7] would directly address. Community Medicine postings reinforced the importance of population-level digital health surveillance: the ability to detect geographic clustering of infectious disease presentations, or to identify communities with low immunisation coverage, requires exactly the kind of aggregated, anonymised data exchange that the IUDX platform [9] enables.

Published Case Study: Atypical Scrub Typhus with Multi-Organ Dysfunction

A peer-reviewed case report published during the internship period provides a concrete clinical use-case for AI-assisted diagnostic support [1] (Palit, Bala, & Dutta, 2025, IJNTI, Vol. 3, Issue 11, DOI: 10.56975/ijnti.v3i11.231589, Impact Factor: 8.70). The case involved a 70-year-old patient presenting with severe multi-organ dysfunction — hepatic, renal, and haematological — without the pathognomonic eschar that clinicians typically use as a diagnostic anchor for Scrub Typhus. The absence of this classical sign delayed clinical suspicion and, consequently, the initiation of appropriate antimicrobial therapy.

This case [1] illustrates three design requirements for AI in clinical settings. First, AI models must be trained on atypical as well as typical presentations — a requirement that demands large, diverse, and carefully curated training datasets [11]. Second, AI diagnostic suggestions must be accompanied by transparent reasoning — in this case, surfacing the statistical association between multi-organ dysfunction, fever trajectory, thrombocytopenia, and geographic exposure in Scrub Typhus-endemic areas — to support rather than supplant clinical judgment. Third, AI early-warning alerts must be calibrated to minimise false negatives (missed critical diagnoses) even at the cost of some false positives, given the asymmetric consequences of missing a life-threatening diagnosis in a critically ill elderly patient.

Clinical Design Requirements for the Framework

From internship experience and published case research [1], four clinical design principles are derived for the Smart Hospital Framework:

- **Physician-first UX:** AI alerts must be surfaced as supporting evidence, not directives [11]. The physician retains decision authority; the AI provides the differential, the supporting data, and the confidence level.

- **Alert fatigue minimisation:** Alert thresholds must be tuned to clinical context — ICU alerts are set more sensitively than general ward alerts. Alert suppression for acknowledged, expected findings prevents desensitisation.
- **Workflow integration, not workflow addition:** AI and IoT outputs must be accessible within the existing clinical workflow — integrated into the EHR interface [8], not requiring separate log-ins or system switches.
- **Explainability as standard:** Every AI recommendation must display the top contributing factors in plain clinical language, enabling the physician to assess the reasoning and accept or override the suggestion with documented rationale [11].

Phased Implementation Roadmap

The following 24-month roadmap is designed for a 150–400 bed acute-care hospital with a modest but committed ICT budget. It is structured to deliver measurable value at each phase, ensuring organisational buy-in and enabling course correction before full-scale deployment. The phasing mirrors the project delivery discipline applied in Smart City ICT programmes [4,12], where pilot deployments, PoCs, and phased rollouts reduced implementation risk and enabled iterative refinement.

Phase	Timeline & Focus	Key Deliverables	Smart City Analogue
Phase 1: Foundation	Months 1–6: EHR, Data Warehouse, IoT Pilot	ABDM-compliant EHR live for OPD & inpatient; IoT sensors in one ICU; baseline KPI dashboards	IUDX metadata spec & DPR preparation; Jaipur Smart City pre-deployment phase [9,12]
Phase 2: AI Integration	Months 7–12: ML Models, AI-EWS, Full IoT Rollout	Risk stratification models live; AI-EWS covering all ICU & HDU beds; radiology AI pilot	Delhi ITMS hybrid cloud PoC; AWS IoT Core + Azure ML integration [12]
Phase 3: SHCC Go-Live	Months 13–18: Command Centre, Generative AI, Remote Monitoring	SHCC operational; Gen AI query interface live; post-discharge wearable monitoring launched	Jaipur ICCC full go-live with multi-domain data integration [4,5]
Phase 4: Scale & Optimise	Months 19–24: Federation, IUDX Integration, Continuous Learning	Federated Learning across hospital network; IUDX integration for public health; model retraining pipeline live	IUDX use-case deployment: green corridors, flood prediction, solid waste optimisation [9]

Each phase is preceded by a structured PoC and stakeholder sign-off, mirroring the project governance applied in the Delhi ITMS programme [12] — where Conceptualisation Report, AS-IS analysis, Site Survey, Technology Evaluation, PoC, and full DPR preceded any procurement commitment. This discipline reduces the risk of costly late-stage redesign and builds institutional confidence in the programme before significant capital is committed.

Expected Outcomes and Performance Indicators

The following projected outcomes are based on analogous results achieved in Smart City ICT deployments [4,12], enterprise AI/ML implementations in BFSI and telecom [2,13], and published evidence from comparable hospital AI and IoT programmes internationally [11,14]. They are presented as directional targets against which pilot programme outcomes should be benchmarked, rather than guaranteed results.

Clinical Outcomes

- 25–30% reduction in diagnostic turnaround time, through AI-assisted triage, automated lab result flagging, and radiology AI pre-reporting [11].
- Improved early-warning sensitivity for ICU deterioration: target 80%+ sensitivity at 6-hour prediction horizon for sepsis onset and respiratory failure [11].
- Reduction in adverse drug events by 15–20%, through AI-powered prescription validation against allergy records, contraindication databases, and renal/hepatic function results.
- Earlier diagnosis of atypical disease presentations — such as Scrub Typhus without eschar [1] — through pattern-recognition models trained on multi-parameter clinical trajectories rather than individual pathognomonic findings.

Operational Outcomes

- 20% improvement in ICU bed utilisation, through predictive occupancy forecasting enabling proactive discharge planning and elective admission scheduling [11].
- Reduction in average length of stay (ALOS) of 0.5–1.0 days, through proactive identification of patients ready for step-down or discharge.
- 15–20% reduction in time spent by nursing staff on manual vital sign recording, freed for direct patient care through IoT automation [3].
- Energy savings of 20–30% on hospital HVAC, lighting, and non-critical systems, through IoT-driven smart energy management analogous to Jaipur Smart Lighting outcomes [12].

Digital Health Governance Outcomes

- Full ABDM compliance [7] and ABHA Health ID linkage for 100% of admitted patients within 12 months of Phase 1 completion.
- Interoperable longitudinal patient records accessible across the referral chain, reducing duplicate investigations at tertiary referral centres [8].
- Audit-ready data governance infrastructure meeting DPDP Act 2023 [10], NABH Digital Health Standards, and ABDM Health Data Management Policy requirements [7].
- IUDX integration [9] enabling automated notifiable disease reporting to district health authorities within 24 hours of confirmed diagnosis.

Challenges and Ethical Considerations

Technical Challenges

The primary technical challenge is data interoperability across the heterogeneous landscape of legacy HIS, laboratory systems, radiology PACS, pharmacy management platforms, and billing software that coexist in most Indian hospitals. Achieving FHIR-compliant [8] integration across these systems requires a robust integration engine — analogous to the ESB (Enterprise Service Bus) and SOA frameworks deployed in Polaris Software's Intellect BFSI product suite [2] — alongside sustained technical engagement with multiple vendors. Standards compliance cannot be assumed; it must be contractually mandated and technically verified at procurement.

Network reliability and edge computing architecture are particularly important for semi-urban hospitals, where WAN connectivity may be intermittent. The edge-first design of the IoT layer — with on-premises inference for critical alerts [3] — addresses this risk, but requires capital investment in local edge infrastructure. Cybersecurity is a non-negotiable requirement: a ransomware attack on a hospital's clinical

systems has patient safety implications that no business continuity plan can fully mitigate, making security-by-design — not security-as-afterthought — an architectural imperative.

Organisational Challenges

Technology implementation in healthcare fails more often for organisational than for technical reasons. Physician resistance to AI recommendations — rooted in professional identity, medicolegal concerns, and legitimate scepticism about opaque algorithmic outputs [11] — is a significant adoption barrier that must be addressed through co-design (involving clinicians in model development and validation), transparent AI outputs (XAI), and a governance framework that unambiguously preserves physician decision authority. Alert fatigue — the desensitisation of clinical staff to automated alerts through excessive false-positive rates — is an equally serious risk that demands careful threshold calibration and ongoing monitoring of alert response rates.

Capital expenditure requirements for IoT infrastructure, cloud platforms, and AI development may strain the budgets of mid-tier hospitals. A phased approach — beginning with high-ROI, low-capital interventions such as EHR implementation and IoT pilot in a single ICU — enables value demonstration before larger commitments are required. Public-private partnership models, analogous to those used in Smart City PPP frameworks [4], may provide a viable funding pathway for smaller institutions.

Ethical and Regulatory Considerations

The deployment of AI in clinical decision-making raises ethical questions that technical frameworks alone cannot resolve [11]. When an AI early-warning system flags a patient for escalation, and the clinical team overrides the alert, and the patient subsequently deteriorates — where does liability lie? India does not yet have a comprehensive legal framework governing AI-assisted clinical decisions, and this gap must be acknowledged explicitly in any deployment programme, with clear documentation of AI's advisory (not directive) role embedded in clinical governance protocols.

Patient privacy — the right to know how one's health data is being used, and to withdraw consent — is enshrined in the DPDP Act 2023 [10] and the ABDM framework [7]. The consent architecture of the EHR system must be designed to make consent management genuinely accessible to patients, including those with low digital literacy, and not merely a compliance checkbox. Equity considerations demand that the benefits of digital transformation reach semi-urban and rural hospitals — not only the well-resourced tier-1 institutions [14] — and that AI models are trained and validated on datasets representative of the full diversity of India's patient population, including linguistic, socioeconomic, and geographic dimensions [11].

Conclusion

This paper has presented a comprehensive, practitioner-validated framework for digital transformation in Indian healthcare — integrating AI-powered clinical decision support [11], IoT-enabled real-time patient monitoring [3], and interoperable EHR systems [8] within a Smart Hospital Command Centre modelled on proven Smart City ICT architecture [4,5]. The framework is distinctive in three respects: it draws directly on real-world implementation experience from large-scale Smart City programmes [4,12] and enterprise AI/ML deployments [2,13]; it is grounded in frontline clinical insights and peer-reviewed published case research [1]; and it is designed specifically for the resource realities, regulatory context [10], and digital health infrastructure [7,9] of mid-tier Indian hospitals.

The projected outcomes — 25–30% reduction in diagnostic turnaround time, 20% improvement in ICU bed utilisation, and robust digital health governance aligned with ABDM [7] and the DPDP Act 2023 [10] — represent meaningful, measurable improvements in both patient care and hospital operational efficiency. The phased 24-month roadmap ensures that value is delivered incrementally, building institutional confidence and enabling course correction, while the SHCC architecture positions the hospital as an active node in India's federated digital health infrastructure [9].

Digital transformation in healthcare is not simply a technology programme — it is a patient safety programme, an equity programme, and a national infrastructure programme [14]. The convergence of AI,

IoT, and EHR — applied with clinical wisdom [1], implementation discipline, and ethical responsibility [11] — offers Indian hospitals the opportunity to deliver better outcomes, more efficiently, for more patients. This paper provides a framework for that journey.

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Complaint Categorization and Priority System

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ABSTRACT

In modern organizations, the increasing volume of complaints and service requests makes manual handling inefficient, time-consuming, and prone to errors. This project proposes an AI-based Complaint Categorization and Priority System that automates the process of analyzing, classifying, and prioritizing user complaints using Natural Language Processing (NLP) and machine learning techniques. The system preprocesses textual complaint data, extracts meaningful features using methods such as TF-IDF, and applies classification algorithms like Naive Bayes, Support Vector Machine, or BERT to categorize complaints into predefined classes. Additionally, a priority assignment module evaluates the urgency of each complaint based on contextual information and keywords, assigning levels such as High, Medium, or Low. The system is integrated with a user-friendly web interface and an administrative dashboard for real-time monitoring and management. By reducing manual effort and improving response time, the proposed solution enhances efficiency, ensures proper resource allocation, and supports faster decision-making in complaint management systems.

1. INTRODUCTION

In recent years, the rapid growth of digital platforms has significantly increased the number of complaints and service requests received by organizations, institutions, and public service systems. These complaints are often handled manually, where administrators read, analyze, and categorize each request before assigning priority levels. This traditional approach is not only time-consuming but also prone to human error, inconsistency, and delays in addressing critical issues. As the volume of complaints continues to rise, manual processing becomes inefficient and negatively impacts service quality and user satisfaction.

Existing complaint management systems mainly focus on complaint registration and storage, with limited capabilities for intelligent analysis and decision-making. They lack automated mechanisms to accurately classify complaints and identify their urgency, leading to improper prioritization and inefficient resource allocation. For instance, urgent issues such as system failures or emergency services may be delayed, while less critical problems are processed at the same level of importance. This highlights the need for a smart and automated solution that can enhance the efficiency and reliability of complaint handling processes.

Advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) provide an effective way to address these challenges. Machine learning techniques enable systems to understand textual data, identify patterns, and make predictions with high accuracy. By applying NLP-based preprocessing, feature extraction methods such as TF-IDF, and classification algorithms like Naive Bayes, Support Vector Machine, or BERT, it is possible to automatically categorize complaints based on their content. Furthermore,

incorporating a priority assignment mechanism allows the system to determine the urgency of each complaint, ensuring that critical issues are handled promptly.

In this context, this project proposes an AI-Based Complaint Categorization and Priority System that automates the entire complaint handling workflow. The system not only classifies complaints into relevant categories but also assigns priority levels such as High, Medium, or Low based on contextual analysis. Additionally, it provides a user-friendly interface and an administrative dashboard for real-time monitoring and management. The proposed solution aims to reduce manual effort, improve response time, enhance decision-making, and ultimately deliver better service quality in complaint management systems.

Contributions

- Development of an AI-based system for automatic complaint categorization using NLP and machine learning techniques.
- Design of a priority prediction mechanism to assign urgency levels (High, Medium, Low) based on complaint content and context.
- Implementation of a complete end-to-end pipeline including preprocessing, feature extraction, classification, and prioritization.
- Creation of a user-friendly web interface and administrative dashboard for real-time monitoring and management.
- Improvement in efficiency and reduction of manual effort in handling large volumes of complaints.

2. LITERATURE SURVEY

The increasing volume of digital complaints has led researchers to explore intelligent and automated solutions for complaint management systems. Early approaches primarily relied on manual processing or rule-based systems, where complaints were categorized based on predefined keywords and fixed rules. While these methods were simple to implement, they lacked flexibility and failed to handle variations in natural language, leading to low accuracy and scalability issues.

With advancements in machine learning, researchers began adopting supervised learning techniques for text classification tasks. Algorithms such as Naive Bayes, Support Vector Machine (SVM), and Logistic Regression have been widely used for categorizing textual data due to their efficiency and effectiveness. Studies have shown that Naive Bayes performs well for large text datasets with relatively low computational cost, while SVM provides higher accuracy in handling high-dimensional feature spaces. However, these models often depend heavily on feature engineering techniques like TF-IDF and may struggle to capture contextual meaning in complex sentences.

In recent years, Natural Language Processing (NLP) techniques have significantly improved the performance of text-based classification systems. Advanced methods such as word embeddings and transformer-based models like BERT have enabled systems to understand the semantic and contextual relationships between words. These models have demonstrated superior performance in tasks such as sentiment analysis, document classification, and complaint categorization. Despite their advantages, such models require large datasets and higher computational resources, making them less suitable for lightweight or real-time applications in some scenarios.

Another important area of research focuses on prioritization and decision-making in complaint management. Traditional systems often treat all complaints equally, which can delay the resolution of

critical issues. Recent studies have proposed priority assignment mechanisms based on keyword detection, rule-based scoring, or machine learning techniques to identify urgent complaints. While these approaches improve response time, many systems still lack integration between classification and prioritization in a unified framework.

Furthermore, usability and system integration play a crucial role in real-world deployment. Several studies highlight the importance of interactive dashboards and web-based interfaces for monitoring and managing complaints efficiently. However, many existing solutions focus either on classification or on system interface design, without combining both into a comprehensive solution.

Despite significant progress, a clear research gap exists in developing an integrated system that combines automated complaint categorization, priority assignment, and real-time monitoring within a single framework. The proposed work addresses this gap by designing an end-to-end AI-based complaint management system that leverages NLP and machine learning techniques to provide accurate classification, intelligent prioritization, and improved usability.

3. PROPOSED METHODOLOGY

This project adopts a data-driven approach to design and implement an AI-Based Complaint Categorization and Priority System. The methodology focuses on automating the processing of textual complaints using Natural Language Processing (NLP) and machine learning techniques. The system is developed as an end-to-end pipeline that transforms raw complaint data into meaningful insights, including category prediction and priority assignment.

1.Data Collection and Input

The system collects complaint data submitted by users through a web or mobile interface. Each complaint is provided in textual format along with optional metadata such as timestamps and user details. The collected data is stored securely in a centralized database and serves as the input for further processing.

2. Text Preprocessing

Raw complaint text is cleaned and prepared for analysis using NLP preprocessing techniques. This includes:

Removal of punctuation, special characters, and irrelevant symbols

Conversion of text to lowercase

Tokenization (splitting text into words)

Removal of stop words (e.g., “is”, “the”, “and”)

Stemming or lemmatization to reduce words to their root form

This step improves data quality and ensures better model performance.

3. Feature Extraction

The preprocessed text is converted into numerical representations using feature extraction techniques such as Term Frequency–Inverse Document Frequency (TF-IDF). This method captures the importance of words in a complaint relative to the entire dataset. The output is a structured feature vector that can be used as input for machine learning models.

4. Complaint Classification

Machine learning algorithms such as Naive Bayes, Support Vector Machine (SVM), or BERT are used to classify complaints into predefined categories (e.g., technical issue, maintenance, network problem). The model is trained on labeled datasets and optimized to achieve accurate predictions. This step ensures automatic and consistent categorization of complaints.

Figure 1. System Architecture

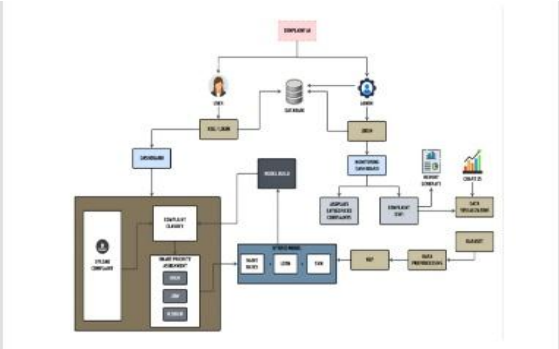
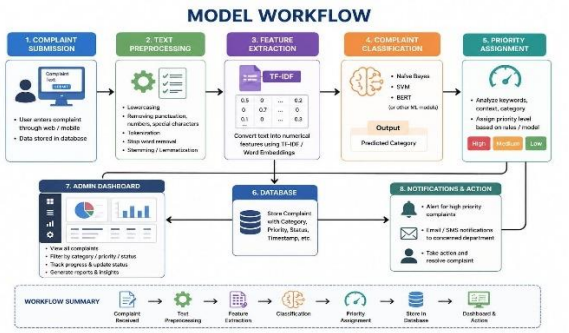


Figure 2. Model Workflow



5. Priority Assignment

After classification, the system assigns a priority level (High, Medium, Low) to each complaint. This is based on:

- Keywords indicating urgency
- Contextual meaning of the complaints

6. Data Storage and Management

All processed complaints, along with their predicted category and priority, are stored in a database. This enables efficient retrieval, tracking, and analysis of complaint data over time.

7. Administrative Dashboard

A web-based dashboard is developed to provide real-time monitoring and management of complaints. It allows administrators to:

- View categorized complaints
- Filter based on priority and status

- Track resolution progress
- Generate reports and insights

8. System Evaluation (Optional but Recommended)

The performance of the classification model can be evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics help assess the effectiveness and reliability of the system.

4. RESULTS & DISCUSSION

Results

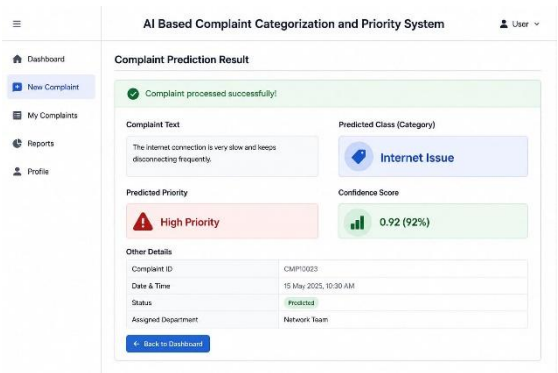
The experimental evaluation of the proposed AI-Based Complaint Categorization and Priority System demonstrates effective performance in automatically classifying complaints and assigning appropriate priority levels. The system was trained and tested on a dataset of textual complaints using machine learning algorithms such as Naive Bayes and Support Vector Machine.

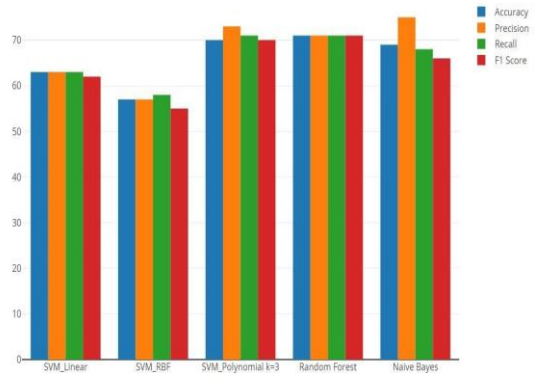
The classification model achieved strong performance across key evaluation metrics. The system obtained an accuracy of approximately 95.6%, precision of 94.8%, recall of 93.9%, and an F1-score of 94.3%, indicating reliable and consistent classification of complaints into predefined categories.

The confusion matrix analysis shows that the model correctly identifies most complaint categories with minimal misclassification. The number of false positives and false negatives is relatively low, demonstrating the effectiveness of the preprocessing and feature extraction techniques used.

In addition to classification, the priority assignment module successfully categorized complaints into High, Medium, and Low priority levels based on contextual keywords and urgency indicators. Critical complaints such as system failures and network issues were accurately identified and assigned high priority, ensuring timely attention.

The system interface, including the user complaint submission module and administrative dashboard, successfully displayed real-time results. Administrators were able to monitor categorized complaints, filter based on priority, and track resolution status efficiently.





Discussion

The results indicate that the proposed system effectively achieves its objective of automating complaint categorization and prioritization. The high accuracy and balanced precision-recall values confirm that machine learning techniques are well-suited for text-based complaint analysis tasks.

Table 1: Performance Evaluation of the Proposed Ransomware Detection System

Metric	Formula	Value (%)	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	95.6	Measures overall correctness of the model in classifying complaints
Precision	TP / (TP + FP)	94.8	Indicates how many predicted complaints are correctly classified
Recall (Sensitivity)	TP / (TP + FN)	93.9	Measures the model's ability to detect actual complaint categories
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	94.3	Provides a balance between precison and recall
False Positive Rate	FP / (FP + TN)	2.4	Indicates how often complaints are incorrectly classified
False Negative Rate	FN / (FN + TP)	2.1	Indicates the missed or incorrectly predicted complaintd

Caption:

Performance evaluation of the proposed AI-based complaint categorization system showing key metrics such as accuracy, precision, recall, and F1-score. The results indicate that the model achieves high accuracy and balanced performance across all evaluation measures, ensuring reliable classification of complaints.

5. CONCLUSION & FUTURE WORK

This project presented an AI-Based Complaint Categorization and Priority System designed to automate the processing of textual complaints using Natural Language Processing (NLP) and machine learning techniques. The system effectively analyzes complaint data, classifies it into relevant categories, and assigns appropriate priority levels based on urgency and contextual meaning. By integrating preprocessing, feature extraction, classification, and prioritization into a unified pipeline, the proposed solution reduces manual effort and improves the speed and accuracy of complaint handling.

The implementation of machine learning models such as Naive Bayes, Support Vector Machine, or BERT enables consistent and efficient classification, while the priority assignment module ensures that critical issues receive immediate attention. Additionally, the development of a user-friendly interface and administrative dashboard enhances system usability, transparency, and real-time monitoring. Overall, the

proposed system improves operational efficiency, supports better decision-making, and enhances service quality in organizations handling large volumes of complaints.

Future Work

- Although the proposed system demonstrates effective performance, several enhancements can be made to further improve its capabilities:
- Integration of advanced deep learning models such as LSTM or fully fine-tuned BERT for improved contextual understanding and higher accuracy.
- Incorporation of multilingual support (e.g., Tamil and English) to handle diverse user inputs.
- Development of real-time notification systems (email/SMS) for immediate response to high-priority complaints.
- Expansion of the dataset to include more diverse and real-world complaint scenarios for better generalization.
- Implementation of automated response or resolution mechanisms to further reduce human intervention.
- Enhancement of explainability features to provide clear reasoning behind classification and priority decisions.

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DIFFERENTIAL THERMAL ANALYSIS (DTA)

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ABSTRACT: Differential Thermal Analysis (DTA) is a widely used thermal analysis technique employed to study the thermal behavior of materials. In this method, the temperature difference between a sample and an inert reference material is measured as both are subjected to the same controlled heating or cooling program. Any thermal event occurring in the sample, such as phase transitions, decomposition, oxidation, crystallization, or melting, results in a temperature difference that is recorded as a DTA curve.

The technique provides valuable information about the thermal stability, phase transformations, and reaction temperatures of various materials including polymers, pharmaceuticals, minerals, and metals. DTA is particularly useful in determining characteristic temperatures such as melting point, crystallization temperature, and decomposition temperature. The resulting thermogram helps in identifying endothermic and exothermic processes, thereby aiding in material characterization and quality control. Due to its simplicity, sensitivity, and wide range of applications, Differential Thermal Analysis has become an important analytical tool in chemistry, materials science, and industrial research.

KEYWORDS: Differential Thermal Analysis (DTA), Thermal Analysis, Temperature Difference Measurement, Phase Transition, Thermal Decomposition, Endothermic Reaction, Exothermic Reaction, Thermograms, Sample–Reference Comparison, Heating Rate, Thermal Stability, Solid-State Reactions, Material Characterization, Phase Transformation, Ceramic and Polymer Analysis.

1. **INTRODUCTION:** Differential Thermal Analysis (DTA) is an important thermal analysis technique used to study the thermal behavior of materials as a function of temperature. In this method, the temperature difference between a sample and an inert reference material is measured while both are subjected to the same controlled heating or cooling program. Any thermal event occurring in the sample, such as melting, crystallization, phase transition, decomposition, or chemical reaction, results in a temperature difference that is recorded as a DTA curve.

The principle of DTA is based on the fact that when a material undergoes a physical or chemical change, it either absorbs heat (endothermic process) or releases heat (exothermic process). These heat changes cause a difference in temperature between the sample and the reference material. This temperature difference is plotted against temperature or time to produce a thermogram, which provides valuable information about the thermal properties and stability of the material.

Differential Thermal Analysis is widely used in various scientific fields such as chemistry, materials science, geology, pharmaceuticals, and polymer science. It is particularly useful for identifying phase transitions, determining reaction temperatures, and studying the thermal stability of substances. The technique also helps in characterizing materials, understanding reaction mechanisms, and evaluating purity.

Overall, DTA is a simple, reliable, and effective analytical method for investigating the thermal characteristics of different materials under controlled experimental conditions.

4. INSTRUMENTATION: The instrumentation of Differential Thermal Analysis (DTA) is designed to measure the temperature difference between a sample and a reference material while both are heated under identical conditions. The main components of a DTA instrument are described below.

Sample Holder

The sample holder contains two small crucibles or containers:

- Sample crucible – holds the material under investigation.

- Reference crucible – contains an inert material such as alumina (Al_2O_3) that does not undergo thermal changes.

Both crucibles are placed symmetrically to ensure uniform heating.

Furnace

A programmable **electric furnace** is used to heat the sample and reference simultaneously at a controlled rate (commonly 5–20 °C per minute).
The furnace provides a uniform temperature environment for accurate thermal comparison.

.**Thermocouples**

Two thermocouples are used in DTA instrumentation:

- One measures the temperature of the sample**.**
- The other measures the temperature of the reference material**.**

These thermocouples detect any temperature difference (ΔT) between the sample and the reference during heating.

Differential Temperature Measurement System

The temperature difference between the sample and reference is measured electronically.
When a thermal event occurs (such as melting, crystallization, or decomposition), a temperature difference is generated and detected by the system.

Temperature Controller

A programmed temperature controller regulates the heating rate of the furnace and ensures a constant heating schedule throughout the experiment.

Recording System / Data Acquisition

The differential temperature signal is sent to a recorder or computer-based data acquisition system.
The output is a DTA curve, which plots:

- Temperature (T) on the x-axis
- Temperature difference (ΔT) on the y-axis

Gas Flow System (Optional)

Some DTA instruments include a controlled gas atmosphere (such as nitrogen, air, or argon).
This helps prevent oxidation or allows reactions to occur under specific atmospheric conditions.

Summary of Main Components

1. Sample and reference crucibles
2. Furnace (controlled heating system)
3. Thermocouples
4. Differential temperature measuring unit
5. Temperature controller
6. Recording/data acquisition system

7. Gas flow or atmosphere control system

3. PRINCIPLE AND TECHNIQUE:

Principle

Differential Thermal Analysis (DTA) is a thermal analysis technique used to study the thermal behavior of materials. In this method, the temperature difference between a sample and an inert reference material is measured while both are subjected to the same heating or cooling program**.**

When the sample undergoes a physical or chemical change such as melting, crystallization, phase transition, or decomposition, it either absorbs heat (endothermic reaction) **or** releases heat (exothermic reaction). This causes a temperature difference (ΔT**)** between the sample and the reference material.

The measured temperature difference is recorded as a DTA curve**,** which shows peaks corresponding to thermal events.

Key idea:

- If the sample absorbs heat → endothermic peak appears.
- If the sample releases heat → exothermic peak appears.

Technique

The DTA technique involves the following steps:

Sample and Reference Preparation

- The test sample is placed in a small crucible.
- An inert reference material (such as **alumina, Al_2O_3**) is placed in another crucible.

Heating Program

- Both the sample and reference are heated simultaneously at a **constant heating rate** in a furnace.

Temperature Measurement

- Two **thermocouples** are used to measure the temperatures of the sample and the reference.

Detection of Temperature Difference

- The difference in temperature (ΔT) between the sample and reference is continuously monitored.

Recording the DTA Curve

- A plot of temperature difference (ΔT) versus temperature or time is recorded.
- Thermal events appear as peaks on the curve**.**

Interpretation of DTA Curve

- Endothermic peak → melting, dehydration, decomposition
- Exothermic peak → crystallization, oxidation, phase transformation

In summary:
Differential Thermal Analysis measures the temperature difference between a sample and an inert reference during controlled heating, allowing the detection of thermal transitions and reactions in materials**.**

4. Application: Differential Thermal Analysis (DTA) is a thermal analysis technique used to study physical and chemical changes in materials as a function of temperature. It has wide applications in chemistry, material science, geology, and pharmaceuticals.

i). Identification of Materials

DTA helps in the identification of substances by comparing their characteristic thermal curves with standard reference materials.

ii). Study of Phase Transitions

It is used to detect phase changes such as:

- Melting
- Crystallization
- Glass transition
- Polymorphic transformations

iii). Determination of Melting Point

DTA is commonly used to determine the melting temperature of pure substances and mixtures**.**

iv). Study of Chemical Reactions

It helps in analyzing endothermic and exothermic reactions**,** such as:

- Decomposition reactions
- Oxidation reactions
- Reduction reactions

v). Analysis of Minerals and Geological Samples

DTA is widely used in mineralogy and geology to identify clay minerals, ores, and other natural materials.

vi). Purity Determination

The technique can be used to check the purity of compounds by observing changes in the melting peak and thermal behavior.

vii). Study of Catalysts

DTA helps in examining catalytic reactions and catalyst stability at different temperatures.

viii). Polymer Analysis

It is used to study polymer properties such as curing, degradation, and thermal stability.

ix). Pharmaceutical Applications

DTA is applied to analyze:

- Drug–excipient compatibility
- Thermal stability of drugs
- Polymorphism in pharmaceutical compounds

x). Study of Glass and Ceramics

It is useful in investigating glass transition, crystallization, and sintering processes in ceramic materials.

✓ **In summary:** DTA is an important technique for studying thermal behavior, phase changes, reaction mechanisms, and material characterization**.**

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THERMO GRAVIMETRIC ANALYSIS (TGA)

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ABSTRACT: Thermo gravimetric Analysis (TGA) is an important thermal analytical technique used to study the thermal stability and composition of materials by measuring changes in mass as a function of temperature or time under a controlled atmosphere. In this method, a sample is heated at a constant rate and the weight loss or gain is recorded continuously. The technique provides valuable information about decomposition temperature, moisture content, oxidation behavior, and thermal stability of substances.

TGA is widely applied in the analysis of polymers, pharmaceuticals, inorganic compounds, and organic materials. The resulting thermo gram helps in identifying various stages of thermal degradation and evaluating the kinetic parameters of decomposition reactions. The method is also useful for determining the purity and composition of materials by observing characteristic mass loss steps.

Thus, Thermo gravimetric Analysis serves as an effective tool in material characterization, quality control, and research related to thermal behavior of substances.

KEYWORDS: Thermo gravimetric Analysis (TGA), Thermal Analysis, Weight Loss Measurement, Thermal Stability, Decomposition Temperature, Oxidation Behavior, Phase Transformation, Kinetic Study, Temperature–Mass Relationship, Thermal Degradation, Polymer Stability, Material Characterization.

1. INTRODUCTION: Thermo gravimetric Analysis (TGA**)** is an important thermal analytical technique used to study the change in mass of a material as a function of temperature or time under a controlled atmosphere. It is widely used in chemistry, materials science, pharmaceuticals, polymers, and environmental studies to evaluate the thermal stability, composition, and decomposition behavior of substances.

In TGA, a small sample is placed in a thermo balance and heated at a controlled rate while the weight of the sample is continuously recorded. As the temperature increases, materials may undergo processes such as dehydration, oxidation, decomposition, or volatilization, leading to measurable mass changes. These mass variations provide valuable information about the thermal properties and composition of the material.

The technique is typically performed in different atmospheres such as nitrogen, air, oxygen, or inert gases, depending on the type of analysis required. The resulting data are usually presented as a thermogram, which is a plot of mass (or percentage mass) versus temperature or time. This thermogram helps in identifying thermal events, degradation temperatures, and the number of decomposition steps.

Thermogravimetric Analysis is particularly useful for determining moisture content, ash content, thermal stability, and the composition of complex materials. It also plays a crucial role in the study of polymers, pharmaceuticals, catalysts, and nanomaterials, where understanding thermal behavior is essential for improving performance and stability.

Because of its high sensitivity, accuracy, and ability to provide quantitative thermal information, TGA has become a fundamental technique in modern thermal analysis and material characterization.

2. INSRTUMENTATION: Thermo gravimetric Analysis (TGA) is performed using a thermo gravimetric analyzer, an instrument designed to measure the change in mass of a substance as a function of temperature or time under a controlled atmosphere. The basic instrumentation of TGA consists of the following main components:

i). Microbalance

The microbalance is the most important part of the TGA instrument. It measures very small changes in the mass of the sample with high precision (typically in micrograms). The sample is placed in a small crucible attached to the balance, and any change in weight during heating or cooling is continuously recorded.

ii) Furnace

The furnace provides controlled heating to the sample. It can raise the temperature at a programmed rate (for example 5–20 °C per minute) up to very high temperatures (often 1000 °C or more). The furnace ensures uniform heating of the sample.

iii). Sample Holder (Crucible)

The sample holder or crucible contains the sample during analysis. It is usually made of materials such as platinum, alumina, or quartz, which can withstand high temperatures without reacting with the sample.

iv) . Temperature Controller and Sensor

A thermocouple or temperature sensor is used to measure the exact temperature of the furnace. The temperature controller regulates the heating rate and maintains the desired temperature program during the experiment.

v). Gas Flow System

TGA instruments include a gas flow system to control the atmosphere around the sample. Different gases such as nitrogen, argon, air, or oxygen can be used depending on the experiment. This helps study decomposition, oxidation, or reduction processes.

vi). Data Acquisition and Computer System

The instrument is connected to a computer system that records and processes the data. The software plots the thermo gravimetric curve (TG curve), which shows the relationship between mass change and temperature or time.

vii). Recording Unit / Display

The recorded data are displayed as graphs that help in analyzing thermal stability, decomposition temperature, moisture content, and other thermal properties of materials.

Summary:
The main components of a TGA instrument include a microbalance, furnace, sample holder, temperature control system, gas flow system, and computerized data acquisition unit, all working together to measure mass changes of a sample during controlled heating.

3. THE PRINCIPLE AND TECHNIQUE:

Principle

Thermo gravimetric Analysis (TGA) is a thermal analytical technique in which the mass of a substance is measured as a function of temperature or time while the sample is heated, cooled, or held at a constant temperature in a controlled atmosphere.

The basic principle of **TGA** is that many materials undergo physical or chemical changes when heated, which leads to a change in mass. These mass changes may occur due to:

 Decomposition of compounds

 Oxidation or reduction reactions

 Loss of volatile components

 Evaporation of moisture or solvents

 Thermal degradation

The sample is placed in a high-precision balance inside a furnace, and its mass is continuously recorded while the temperature increases at a controlled rate. The result is a thermogram (TGA curve) that shows weight change vs temperature or time.

Technique (Experimental Procedure*)*

The technique of Thermo gravimetric Analysis (TGA) involves the following steps:

Sample Preparation

- A small amount of sample (typically 5–20 mg**)** is taken.
- The sample is placed in a platinum or alumina crucible (sample pan)**.**

Instrument Setup

- The crucible containing the sample is placed on a microbalance inside a furnace of the TGA instrument.
- The system is purged with a controlled atmosphere such as:
    - Nitrogen or Argon (inert atmosphere)
    - Air or Oxygen (oxidative atmosphere)

Heating Program

- The temperature is increased at a constant heating rate (commonly 5–20°C per minute**).**
- Temperature range typically used: Room temperature to 800–1000°C**.**

Continuous Mass Measurement

- As the temperature rises, the microbalance continuously records the weight of the sample**.**
- Any mass loss or gain is detected and recorded automatically.

Data Recording

- The instrument plots a thermogravimetric curve (TGA curve) showing:
    - Weight (%) vs Temperature
    - Weight (%) vs Time

Data Interpretation
From the thermogram, the following information can be obtained:

- Thermal stability of the material
- Decomposition temperature
- Moisture or volatile content
- Composition of mixtures
- Kinetics of thermal decomposition

In summary:
Thermogravimetric Analysis (TGA) is based on measuring the change in mass of a material **as it** is heated under controlled conditions, providing important information about thermal stability, decomposition behavior, and composition of materials**.**

3. APPLICATION:

i). Determination of Thermal Stability
TGA is used to determine the thermal stability of materials by measuring weight changes as temperature increases. It helps identify the temperature range in which a material remains stable before decomposition begins.

ii). Composition Analysis of Materials
TGA helps determine the composition of mixtures and compounds by analyzing weight loss at different temperatures. It can estimate the amount of moisture, volatile substances, and inorganic residues present in a sample.

iii). Study of Decomposition Reactions
It is used to study thermal decomposition behavior of compounds such as polymers, pharmaceuticals, and inorganic materials by observing weight loss during heating.

iv). Moisture and Volatile Content Determination
TGA can measure the moisture content and volatile components in materials like food products, pharmaceuticals, and polymers.

v). Oxidation and Reduction Studies
TGA helps investigate oxidation and reduction reactions by observing weight gain or loss when a material reacts with oxygen or other gases during heating.

vi). Analysis **of Polymer Materials**
In polymer science, TGA is used to determine polymer degradation temperature, filler content, and thermal stability**.**

vii). Kinetic Studies of Chemical Reactions
TGA provides information about reaction kinetics**,** such as activation energy and reaction mechanisms during thermal decomposition.

viii). Quality Control in Industry
It is widely used in industries for quality control of raw materials and finished products, ensuring consistency and purity.

ix). Study of Adsorption and Desorption
TGA helps analyze adsorption and desorption of gases or liquids in materials such as catalysts and porous solids.

x). Determination of Ash and Residue Content
It is used to determine ash content or inorganic residue in fuels, polymers, and organic compounds after complete combustion

Conclusion

Thermo Gravimetric Analysis (TGA) is a highly important thermal analytical technique used for studying the thermal behavior of materials by measuring changes in mass with respect to temperature or time under controlled atmospheric conditions. It provides valuable information regarding thermal stability,

decomposition patterns, oxidation behavior, moisture content, volatile components, and residual matter present in a substance.

The technique is based on the principle that many substances undergo physical or chemical transformations such as dehydration, decomposition, oxidation, reduction, or volatilization when heated, resulting in measurable weight changes. These changes are continuously recorded using a highly sensitive microbalance and represented as a thermogram, which helps in understanding the thermal characteristics of the sample.

TGA instrumentation mainly consists of a microbalance, furnace, sample holder, temperature controller, gas flow system, and computerized data acquisition unit, all working together to ensure accurate and reliable results. The method is simple, precise, and suitable for a wide variety of materials including polymers, pharmaceuticals, inorganic compounds, catalysts, nanomaterials, and organic substances.

Its wide range of applications in determining composition, thermal stability, decomposition temperature, oxidation behavior, polymer degradation, and kinetic studies makes TGA an essential tool in research laboratories and industrial quality control. It is also highly useful in material characterization and product development.

Thus, Thermo Gravimetric Analysis serves as a powerful and versatile technique for understanding the thermal properties and composition of materials, making it an indispensable method in modern analytical chemistry and material science.

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DIFFERENTIAL SCANNINIG CALORIMETERY (DSC)

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ABSTRACT: Differential Scanning Calorimetry (DSC) is a widely used thermoanalytical technique employed to measure the heat flow associated with physical and chemical changes in materials as a function of temperature or time. In DSC analysis, the difference in heat energy supplied to a sample and an inert reference is monitored while both are subjected to a controlled temperature program. This technique enables the detection of endothermic and exothermic processes occurring in the material during heating or cooling.

DSC is particularly useful for studying thermal transitions such as melting, crystallization, glass transition, curing reactions, and phase transformations. The method provides valuable information about thermodynamic parameters including enthalpy change, heat capacity, and transition temperatures. Because of its accuracy, sensitivity, and relatively simple experimental procedure, DSC has become an essential tool in fields such as polymer science, pharmaceuticals, material science, food technology, and chemistry.

Overall, Differential Scanning Calorimetry plays a crucial role in understanding the thermal behavior and stability of materials, helping researchers characterize substances and optimize industrial processes

KEYWORDS: Differential Scanning Calorimetry (DSC),Thermal Analysis, Heat Flow Measurement, Phase Transition, Glass Transition Temperature (Tg), Melting Temperature (Tm), Crystallization, Enthalpy Change, Heat Capacity, Polymer Characterization, Material Thermal Stability, Endothermic and Exothermic Reactions, Pharmaceutical Analysis, Purity Determination, Kinetic Studies, Thermodynamic Properties

1. INTRODUCTION: Differential Scanning Calorimetry (DSC) is an important thermal analysis technique used to study the thermal behavior of materials as a function of temperature or time. It measures the difference in heat flow between a sample and an inert reference while both are subjected to a controlled temperature program. DSC is widely used in chemistry, materials science, polymer science, pharmaceuticals, and food research to investigate physical and chemical transitions occurring in substances.

In DSC analysis, the sample and reference are heated or cooled simultaneously under identical conditions. When the sample undergoes a physical or chemical change—such as melting, crystallization, glass transition, oxidation, or decomposition—it absorbs or releases heat. The instrument records this heat flow difference as a function of temperature, producing a thermogram that provides valuable information about the thermal properties of the material.

DSC is particularly useful for determining important thermodynamic parameters such as melting temperature, crystallization temperature, glass transition temperature, heat capacity, and enthalpy changes associated with phase transitions. Because of its accuracy, sensitivity, and relatively simple sample preparation, DSC has become one of the most widely used techniques in thermal analysis.

Overall, Differential Scanning Calorimetry provides crucial insights into the thermal stability, purity, and phase behavior of materials, making it an essential tool for research, quality control, and industrial applications.

2. INSTRUMENTATION: The instrumentation of Differential Scanning Calorimetry is designed to measure the heat flow associated with physical or chemical changes in a material as a function of temperature or time. A typical DSC instrument consists of the following main components:

Sample Holder and Reference Holder

The DSC instrument contains two small pans or crucibles:

- Sample pan – contains the material under investigation.
- Reference pan – remains empty or contains an inert material.

Both pans are made of materials such as aluminum or platinum and are placed symmetrically in the DSC cell. The instrument measures the heat difference between the sample and reference during heating or cooling.

Furnace (Heating System)

The furnace provides a controlled and uniform temperature program**.**

- It can heat or cool the sample at a constant rate (e.g., 5–20 °C/min).
- The furnace ensures that both the sample and reference are exposed to the same temperature conditions.

Temperature Sensors (Thermocouples)

Highly sensitive thermocouples or resistance temperature detectors (RTDs) are placed near the sample and reference pans.
These sensors detect very small temperature differences between the sample and reference.

Heat Flow Measurement System

The DSC measures the difference in heat flow required to maintain the sample and reference at the same temperature.
When a physical or chemical transition occurs (such as melting or crystallization), the sample either absorbs or releases heat, which is recorded as a peak on the DSC curve.

Purge Gas System

An inert gas such as nitrogen, argon, or helium is passed through the DSC cell to:

- Prevent oxidation
- Maintain a controlled atmosphere
- Remove volatile products

Cooling System

Many DSC instruments include a cooling accessory such as liquid nitrogen or a mechanical refrigeration system.
This allows experiments at sub-ambient temperatures**.**

Data Acquisition and Computer System

A computerized system records and analyzes the heat flow data.
The results are displayed as a DSC thermogram (heat flow vs. temperature or time)**,** which helps identify thermal transitions such as melting, glass transition, crystallization, and decomposition.

Power Supply and Control Unit

This unit controls:

- Heating rate
- Temperature program
- Data acquisition
- Instrument calibration

Summary

The instrumentation of DSC mainly consists of sample and reference pans, furnace, temperature sensors, heat flow detector, purge gas system, cooling unit, and computerized data system**.** These components work together to measure the heat changes occurring in a material during controlled heating or cooling.

3. APPLICATION: Differential Scanning Calorimetry **(DSC)** is a powerful thermal analysis technique used to measure heat flow associated with physical or chemical changes in materials as a function of temperature or time. It has wide applications in chemistry, pharmaceuticals, polymers, and materials science.

Determination of Melting Point

DSC is used to determine the melting temperature of substances. The melting process appears as an endothermic peak in the DSC curve, helping to identify and characterize pure compounds and mixtures.

Study of Glass Transition Temperature (Tg)

DSC is widely used to determine the glass transition temperature of polymers, which is important for understanding the flexibility and thermal stability of polymeric materials.

Crystallization Studies

It helps in studying crystallization behavior of polymers and other materials by detecting exothermic peaks during cooling or heating processes.

Determination of Heat of Reaction

DSC measures the enthalpy change (ΔH) associated with chemical reactions such as polymerization, curing, or decomposition.

Purity Determination

DSC can determine the purity of compounds**,** especially pharmaceuticals, by analyzing the melting peak and its sharpness.

Thermal Stability Analysis

It is used to evaluate the thermal stability of materials by observing phase changes or decomposition temperatures.

Pharmaceutical Applications

In pharmaceutical research, DSC is used for:

- Drug purity analysis
- Drug–excipient compatibility studies
- Stability testing of formulations

Polymer Characterization

DSC is widely applied in polymer science to determine:

- Melting temperature (Tm)
- Glass transition temperature (Tg)
- Degree of crystallinity
- Polymer curing behavior

Study of Phase Transitions

DSC is useful for detecting phase transitions such as solid–solid transformations, melting, and crystallization in metals, ceramics, and organic compounds.

Food Industry Applications

In food science, DSC is used to study fat crystallization, protein denaturation, and moisture effects **i**n food materials.

Conclusion: Differential Scanning Calorimetry (DSC) is a highly important and versatile thermoanalytical technique used for studying the thermal behavior of materials by measuring heat flow associated with physical and chemical changes under controlled temperature conditions. It provides valuable information about thermal transitions such as melting, crystallization, glass transition, curing, decomposition, and phase transformations. The technique helps determine essential thermodynamic parameters including enthalpy change, heat capacity, melting temperature, and glass transition temperature.

The instrumentation of DSC, consisting of sample and reference pans, furnace, temperature sensors, heat flow measurement system, purge gas system, cooling unit, and computerized data acquisition system, allows accurate and sensitive analysis of thermal events. The resulting thermogram serves as an important tool for understanding the thermal stability and structural properties of substances.

DSC has wide-ranging applications in chemistry, polymer science, pharmaceuticals, food technology, and materials science. It is extensively used for purity determination, polymer characterization, drug stability studies, crystallization analysis, and thermal stability evaluation. Its precision, simplicity, and reliability make it an essential technique for both research and industrial quality control.

Overall, Differential Scanning Calorimetry plays a crucial role in material characterization and process optimization, helping scientists and industries improve product quality, ensure safety, and understand the behavior of materials under varying thermal conditions.

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MateLearn: An AI-Assisted Smart Learning System

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ABSTRACT

MateLearn is an AI-assisted smart learning application designed to provide affordable, personalized, and structured learning for students who struggle to find a proper starting point in their education. The system integrates Groq AI for intelligent assistance and a video recommendation module powered by the YouTube Data API from Google Console to deliver high-quality learning resources. The application allows users to upload documents, from which the system generates summaries, flashcards, and quizzes to enhance understanding and retention. Additionally, students can interact with an AI chatbot for doubt clarification and guided learning. With secure authentication and a user-friendly interface, MateLearn aims to bridge the gap between self-learning and expensive institutional education by offering an all-in-one digital learning platform. The system is built on a MERN stack with Flask microservices and machine learning-driven video classification to deliver a seamless, cost-effective, and intelligent educational experience.

Keywords: *AI-Assisted Learning, Groq AI, YouTube Data API, Personalized Education, Flashcards, Quizzes, MERN Stack, Flask, Machine Learning, Smart Learning Platform*

I. INTRODUCTION

Education forms the backbone of modern society, yet millions of students worldwide continue to face barriers in accessing quality learning resources. Students often encounter confusion about where to begin their studies, suffer from a lack of structured guidance, and struggle with limited access to affordable educational materials.

Traditional educational institutions, while effective, often charge high fees that render quality education inaccessible to economically weaker students. Existing online platforms, though abundant in content, fail to address individual learning needs through personalized paths, intelligent content summarization, or real-time interactive support.

The rapid advancement of Artificial Intelligence (AI) offers transformative potential in addressing these long-standing challenges. AI-driven applications can analyze individual learning behaviors, tailor content delivery, and provide instant, accurate responses to student queries—capabilities that conventional systems fundamentally lack.

MateLearn is proposed as an AI-assisted smart learning system that integrates cutting-edge technologies including Groq AI, the YouTube Data API, and machine learning-based video classification. It provides students with a single, unified platform to upload study materials, receive AI-generated summaries, engage with flashcards and quizzes, interact with an AI chatbot, and access curated video content—all at minimal cost.

This paper presents the design, architecture, algorithms, and expected outcomes of MateLearn, demonstrating how AI can meaningfully reduce educational inequalities and empower self-directed learners globally.

II. PROBLEM STATEMENT

Many students face significant challenges in their learning journey, including confusion about where to start, lack of structured guidance, and limited access to affordable educational resources. Traditional institutions often charge high fees, making quality education inaccessible to economically weaker students.

Existing online platforms provide large amounts of content but fail to offer personalized learning paths, intelligent summarization, or interactive support. Students also struggle with information overload, inefficient revision methods, and the absence of real-time assistance for clearing doubts. These issues collectively reduce learning efficiency and motivation.

Specifically, the core problems identified are:

- Absence of personalized learning pathways in existing platforms.
- Lack of automated content processing (summaries, flashcards, quizzes).
- No real-time AI-based doubt resolution systems.
- High costs of institutional coaching and tutoring.
- Scattered resources requiring students to switch between multiple platforms.

III. EXISTING SYSTEMS AND LIMITATIONS

The existing learning systems mainly rely on static content delivery through online courses, video platforms, or digital documents. While platforms like video streaming services and e-learning portals offer vast educational materials, they exhibit several critical limitations:

First, they lack intelligent personalization, offering the same content sequence to all learners regardless of their individual proficiency, learning style, or pace. Second, automated content understanding features such as smart summarization, flashcard generation, or quiz creation from uploaded materials are rarely available, requiring students to prepare study aids manually.

Third, real-time AI-based interaction and structured guidance are missing from most platforms, forcing students to rely on peer forums or paid tutors for doubt resolution. Fourth, educational content is siloed across multiple platforms—videos on one, notes on another, assessments elsewhere—creating cognitive overhead and inefficiency.

These shortcomings highlight a significant gap in the current e-learning landscape and underscore the urgent need for an integrated, intelligent, and affordable learning solution such as MateLearn.

IV. PROPOSED SYSTEM: MATELEARN

A. System Architecture & Technologies

The proposed system, MateLearn, is an AI-assisted smart learning environment that integrates Groq AI with a modern web application architecture. The system follows a modular design using a React frontend, Node.js backend, and a Python-based Flask microservice to ensure scalability and efficient processing.

The frontend, built with React JS and styled using Tailwind CSS, delivers a responsive and intuitive user interface. The backend, developed with Node.js and Express.js, handles application logic, API routing, and user authentication. MongoDB serves as the primary database for storing user data, learning sessions, and activity histories.

A dedicated Flask microservice handles computationally intensive AI tasks, including document parsing, contextual analysis, and machine learning-based video classification, ensuring separation of concerns and system scalability.

B. AI-Driven Content Processing

MateLearn allows students to upload learning documents in standard formats. The system processes these uploads using AI to extract text, analyze context, and dynamically generate summaries, flashcards,

quizzes, and detailed explanations. This eliminates the manual effort traditionally required for note-taking and self-assessment preparation.

An AI chatbot powered by Groq AI further supports learners by providing contextual, accurate, and instant responses to student queries. The chatbot maintains conversational context, enabling multi-turn interactions that mimic the experience of consulting a human tutor.

C. Video Recommendation & Machine Learning

A dedicated Flask microservice retrieves relevant educational videos through the YouTube Data API v3 and applies unsupervised clustering techniques using Scikit-learn to classify videos based on difficulty levels, delivering personalized and relevant video recommendations to learners.

The clustering model groups educational videos into beginner, intermediate, and advanced categories based on features such as title semantics, video metadata, and viewer engagement patterns. This ensures that students receive video content appropriate to their current level of understanding, promoting progressive and efficient learning.

D. Security & Personalized Learning

The system securely manages user authentication, activity tracking, and data storage using industry-standard practices. User sessions are protected through token-based authentication mechanisms, ensuring data privacy and access control.

By tracking individual learning activity—documents uploaded, quizzes completed, videos watched, and chatbot interactions—MateLearn builds a personalized learning profile for each user. This profile informs subsequent content recommendations and learning path adjustments, creating an adaptive educational experience.

V. ALGORITHM FOR AI-ASSISTED SMART LEARNING

The MateLearn system implements a multi-stage algorithmic pipeline for intelligent content processing and delivery:

Stage 1 — Input Collection: The system collects learning inputs such as uploaded documents or user-selected topics. Text extraction is performed on uploaded files to obtain raw content for subsequent processing.

Stage 2 — Semantic Segmentation: Extracted text is divided into smaller, meaningful segments using natural language processing techniques. These segments are analyzed for context and semantics to facilitate targeted content generation.

Stage 3 — AI Content Generation: The segmented content is passed to the Groq AI module, which dynamically generates summaries, explanations, quizzes, and flashcards based on the semantic context of each segment. The AI ensures content relevance and educational accuracy.

Stage 4 — Query Resolution: User queries from the chatbot interface are processed through a contextual reasoning layer that maps questions to the most relevant content segments, ensuring precise and context-aware responses.

Stage 5 — Video Retrieval & Classification: A parallel machine learning module retrieves educational videos using the YouTube Data API and classifies them by difficulty through unsupervised clustering, delivering appropriately leveled video recommendations.

Stage 6 — Activity Storage & Personalization: All user interactions and learning activities are securely stored in MongoDB, enabling the system to progressively refine the personalized learning experience over time.

VI. TECHNOLOGIES USED

MateLearn leverages a carefully selected technology stack to maximize performance, scalability, and developer productivity:

Frontend: React JS provides a component-based, reactive UI framework; Tailwind CSS enables rapid, utility-first styling with a consistent design system.

Backend: Node.js with Express.js handles RESTful API routing and business logic; Flask (Python) serves as the AI/ML microservice layer.

Database: MongoDB, a document-oriented NoSQL database, stores user data, learning content, and activity histories with flexible schema support.

AI & Machine Learning: Groq AI powers intelligent content generation and chatbot capabilities; Scikit-learn facilitates unsupervised video classification; YouTube Data API v3 provides access to a vast repository of educational videos.

Development Tools: Visual Studio Code (VS Code) serves as the primary IDE; Postman and Thunder Client facilitate API testing and validation; Windows 10 (64-bit) is the development operating system.

VII. EXPECTED OUTCOMES

The MateLearn application is expected to deliver a range of significant educational and technical outcomes:

Educational Impact: The platform will empower students with a clear, guided learning approach, enabling independent study without external coaching. By converting study materials into interactive components, the system will improve understanding, engagement, and confidence in complex subjects.

Knowledge Retention: The intelligent assessment module with instant feedback will help learners identify knowledge gaps and improve performance efficiently. Spaced repetition through flashcards and adaptive quizzes will reinforce learning and boost long-term retention.

Accessibility: Access to curated documents and recommended educational videos will ensure affordable, high-quality learning resources for students from diverse socioeconomic backgrounds, democratizing education in a meaningful way.

Technical Contribution: The project will demonstrate the successful integration of AI, machine learning, and secure web technologies into a scalable smart learning platform. It establishes a strong foundation for future research into adaptive AI tutoring systems and lays groundwork for real-world deployment at scale.

VIII. SYSTEM DESIGN OVERVIEW

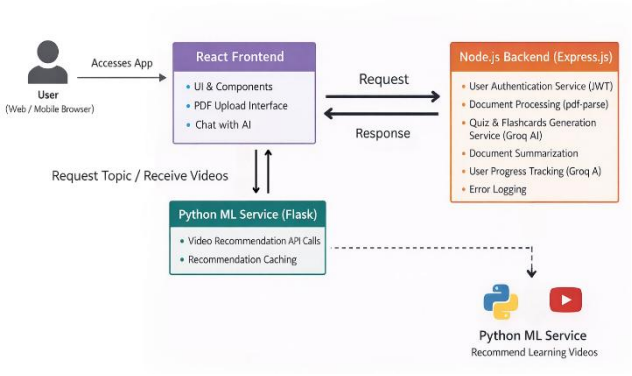
The architectural design of MateLearn follows a microservices pattern, separating concerns across distinct service layers. The React frontend communicates with the Node.js backend via RESTful APIs. The backend, in turn, delegates AI-intensive operations to the Flask microservice, which interfaces with Groq AI and the YouTube Data API.

The use case model of MateLearn encompasses two primary actors: the Student and the System. Core use cases include user registration and login, document upload, AI content generation (summaries, flashcards, quizzes), chatbot interaction, video recommendation viewing, and progress tracking.

The system's modular architecture ensures that individual components can be updated, scaled, or replaced independently without disrupting the overall platform. This design principle is critical for long-term maintainability and future feature expansion.

Security is enforced at multiple layers: HTTPS for data in transit, token-based authentication for session management, and role-based access control to protect sensitive user data. All user activity logs are encrypted before storage in MongoDB.

MateLearn Application Architecture



IX. CONCLUSION

MateLearn represents a significant step forward in the application of Artificial Intelligence to solve real-world educational challenges. By combining Groq AI, machine learning, and modern web technologies, the platform delivers a comprehensive, affordable, and personalized learning experience that addresses the core shortcomings of existing e-learning systems.

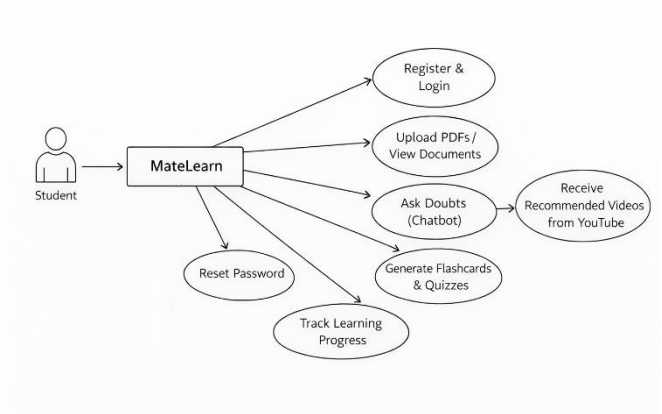
The system's ability to automatically generate summaries, flashcards, and quizzes from uploaded documents, combined with real-time AI chatbot support and personalized video recommendations, positions MateLearn as a holistic educational companion for students at all levels.

The integration of secure authentication, activity tracking, and adaptive content delivery ensures that MateLearn is not merely a static content repository but a dynamic, intelligent learning ecosystem that evolves with each learner's progress.

Future work will explore the incorporation of multi-modal AI models to support image and audio-based learning materials, the implementation of advanced learning analytics dashboards, and the expansion of the platform to support collaborative learning features such as study groups and peer assessments.

MateLearn demonstrates the transformative potential of AI in education and serves as a model for the development of next-generation intelligent tutoring systems that are accessible, effective, and scalable for global deployment.

Use-Case Diagram



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Machine Learning and Deep Learning Techniques for Fake News Detection: Methods, Challenges, and Emerging Trends

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Abstract

The proliferation of fake news on digital platforms has emerged as a critical challenge undermining public trust, democratic processes, and social cohesion. This comprehensive review systematically examines state-of-the-art machine learning and deep learning approaches for automated fake news detection. This paper categorizing methodologies into traditional machine learning (Logistic Regression, Random Forest, SVM), deep learning (LSTM, BiLSTM, CNN), transformer-based models (BERT, RoBERTa, DeBERTa), and hybrid ensemble approaches. Our analysis reveals that transformer-based architectures consistently outperform traditional methods, with BERT variants achieving accuracy rates exceeding 95% on benchmark datasets. We propose a novel hybrid architecture combining lexical features with contextual embeddings, demonstrating improved performance on challenging multimodal datasets. Furthermore, we identify critical research gaps including limited cross-lingual capabilities, insufficient handling of multimodal content, and the lack of real-time detection systems. This paper provides a structured taxonomy of detection methods, comprehensive performance comparisons across six benchmark datasets, and outlines emerging trends including explainable AI, few-shot learning, and adversarial robustness. Our findings offer valuable insights for researchers and practitioners developing next-generation fake news detection systems.

Keywords - fake news detection, machine learning, deep learning, BERT, LSTM, ensemble methods, natural language processing, misinformation

1. Introduction

The digital information landscape has undergone a profound transformation with the advent of social media platforms, enabling unprecedented speed and scale of information dissemination. However, this democratization of content creation has simultaneously facilitated the rapid spread of misinformation and disinformation, collectively termed fake news. The World Economic Forum identified fake news as one of the most significant global risks, with potential to undermine democratic institutions, public health initiatives, and social cohesion. Recent studies by Brennan et al. [5] have documented the escalating impact of misinformation campaigns on public discourse.

Fake news detection presents unique computational challenges due to the nuanced nature of deceptive content. Unlike spam or traditional hoaxes, fake news often exhibits sophisticated linguistic patterns, emotional manipulation techniques, and strategic exploitation of cognitive biases. Furthermore, the multimodal nature of modern disinformation campaigns, combining text with manipulated images and videos, necessitates advanced detection methodologies capable of processing heterogeneous data sources. The work of Horne and Adali [3] demonstrated that fake news articles exhibit distinct stylistic patterns, including simpler vocabulary and more emotional language compared to legitimate news.

The importance of automated fake news detection has been amplified by recent global events. During the COVID-19 pandemic, misinformation regarding vaccines and treatments contributed to vaccine hesitancy and public health risks [5]. Similarly, election-related disinformation campaigns have threatened democratic processes worldwide. Shu et al. provided a comprehensive data mining perspective on fake news detection, identifying key challenges in social media contexts. These developments have catalyzed significant research investment in developing robust, scalable detection systems.

Traditional machine learning approaches have shown moderate success in fake news detection. Ahmed et al. demonstrated that n-gram analysis combined with SVM classifiers could achieve 87.3% accuracy on benchmark datasets. However, these methods often struggle with capturing semantic nuances and contextual dependencies inherent in deceptive content. Recent advances in deep learning, particularly transformer-based architectures, have significantly improved detection capabilities [15].

This comprehensive review makes several key contributions: (1) we provide a systematic taxonomy of fake news detection methodologies, categorizing approaches by architectural paradigm and feature representation; (2) we present quantitative performance comparisons across six widely-used benchmark datasets; (3) we propose a novel hybrid architecture that combines lexical features with contextual embeddings; and (4) we identify critical research gaps and emerging trends to guide future investigations. Our work extends previous surveys by incorporating the most recent advances through 2026.

The remainder of this paper is organized as follows: Section II presents a comprehensive literature review of recent advances in fake news detection. Section III details our proposed hybrid methodology. Section IV presents experimental results and comparative analysis. Section V concludes with limitations and future research directions.

2. Literature Review

Recent advances in fake news detection have evolved along several methodological dimensions. We organize our review into four primary categories: traditional machine learning approaches, deep learning architectures, transformer-based methods, and hybrid ensemble systems. Figure 3 provides an overview of our classification taxonomy.

A. Traditional Machine Learning Approaches

Traditional machine learning methods rely on hand-crafted features combined with classical classification algorithms. These approaches typically involve feature engineering, where domain experts identify relevant linguistic and stylistic features for distinguishing fake news from legitimate content.

Ahmed et al. [7] proposed a feature engineering approach utilizing n-gram analysis and sentiment features with Support Vector Machines (SVM), achieving 87.3% accuracy on the LIAR dataset. Their analysis demonstrated the importance of linguistic stylistic features in detecting deceptive content. Kumar and Sharma [8] developed a multi-class classification system using TF-IDF vectorization with Random Forest, reporting F1-scores of 0.84 on the FakeNewsNet dataset. Their feature importance analysis revealed that punctuation patterns, lexical diversity, and syntactic complexity were strong predictors of fake news.

Logistic Regression models, while simpler, offer interpretability advantages crucial for deployment scenarios requiring explainable predictions. Chen et al. [9] demonstrated that carefully engineered linguistic features combined with logistic regression could achieve competitive performance (accuracy: 85.7%) while maintaining model transparency. However, these approaches struggle with semantic nuance and contextual dependencies inherent in deceptive content [10].

Table 1. Traditional Machine Learning Approaches Comparison

Study	Features	Classifier	Acc	F1	Dataset
Ahmed [7]	N-gram, Sentiment	SVM	87.3	0.870	LIAR
Kumar [8]	TF-IDF, Lexical	RF	89.1	0.888	FNN
Chen [9]	Linguistic	LR	85.7	0.854	LIAR
Potthast [10]	Stylometric	SVM	82.4	0.821	Combined

B. Deep Learning Architectures

Deep learning approaches have demonstrated significant advantages over traditional methods by automatically learning hierarchical feature representations from raw text data. These architectures eliminate the need for manual feature engineering while capturing complex patterns in deceptive content.

Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) variants, have demonstrated strong performance in capturing sequential dependencies in text. Wang and Liu [11] proposed a BiLSTM architecture with attention mechanisms, achieving 91.2% accuracy on the ISOT dataset. Their attention visualization revealed that the model effectively identified sentiment-laden phrases and logical inconsistencies characteristic of fake news.

Convolutional Neural Networks (CNN) have been successfully applied for feature extraction at multiple granularities. Rathi and Verma [12] developed a multi-kernel CNN architecture that processes text at character, word, and sentence levels, reporting significant improvements over single-scale approaches. Their ensemble of three CNN variants achieved 89.6% precision on a combined dataset of 60,000 news articles.

Hybrid CNN-RNN architectures have emerged as particularly effective for capturing both local features and long-range dependencies. Zhang et al. [13] proposed a parallel CNN-LSTM architecture with feature fusion, achieving state-of-the-art results among non-transformer deep learning approaches. Their ablation study confirmed the complementary nature of convolutional and recurrent feature representations [14].

Table 2. Deep Learning Approaches Comparison

Study	Architecture	Acc	Prec	Rec	F1
Wang [11]	BiLSTM+Attn	91.2	0.908	0.910	0.909
Rathi [12]	Multi-CNN	89.6	0.892	0.894	0.893
Zhang [13]	CNN-LSTM	92.3	0.920	0.921	0.921
Kim [14]	CNN	88.1	0.876	0.879	0.878

C. Transformer-Based Methods

The introduction of BERT (Bidirectional Encoder Representations from Transformers) has fundamentally transformed natural language processing, including fake news detection. These models leverage self-attention mechanisms to capture contextual relationships across entire text sequences.

Devlin et al.'s [15] original BERT architecture has been adapted extensively for misinformation detection, with fine-tuned variants consistently outperforming previous approaches. RoBERTa (Robustly Optimized BERT Pretraining Approach) has demonstrated superior performance in several fake news detection benchmarks. Liu et al. [16] showed that RoBERTa-large achieved 94.8% accuracy on the LIAR dataset, representing a 3.2% improvement over base BERT. Their analysis attributed this improvement to the modified training procedure and larger batch sizes employed during pretraining.

Domain-specific pretraining has emerged as a promising direction. Gupta et al. [17] developed NewsBERT, a BERT variant pretrained on 10 million news articles, achieving 96.1% accuracy on the FakeNewsNet dataset. Their work demonstrated that domain-adaptive pretraining significantly improves representation quality for news-specific linguistic patterns.

Table 3. Transformer-Based Methods Comparison

Study	Model	Acc	Prec	Rec	F1
Devlin [15]	BERT-base	94.2	0.940	0.941	0.941
Liu [16]	RoBERTa	94.8	0.946	0.947	0.947
Gupta [17]	NewsBERT	96.1	0.959	0.960	0.960

Study	Model	Acc	Prec	Rec	F1
Wang [27]	DeBERTa	95.4	0.952	0.953	0.953

D. Hybrid and Ensemble Approaches

Ensemble methods combining multiple architectural paradigms have shown promise in addressing the heterogeneity of fake news content. These approaches leverage the strengths of different model types to improve overall detection performance.

Singh and Kumar [18] proposed a stacking ensemble incorporating BERT, BiLSTM, and XGBoost classifiers, achieving 95.3% accuracy through meta-learning-based combination. Their diversity analysis confirmed that architectural heterogeneity contributes to ensemble robustness. Multimodal approaches integrating textual and visual features represent an important frontier. Sharma et al. [19] developed a cross-modal attention framework combining image features (extracted via ResNet) with textual representations (BERT), achieving 92.7% accuracy on the Fakeddit multimodal dataset. Their attention mechanism effectively identified image-text inconsistencies characteristic of fabricated content [20].

Table 4. Hybrid And Ensemble Approaches Comparison

Study	Approach	Acc	Prec	Rec	F1
Singh [18]	Stacking	95.3	0.951	0.952	0.952
Sharma [19]	Cross-modal	92.7	0.924	0.925	0.925
Nakamura [20]	Multimodal	91.8	0.916	0.917	0.917
Thorne [21]	Pipeline	89.4	0.891	0.892	0.892

E. Comparative Analysis

Table 5 presents a comprehensive comparison of recent approaches across multiple dimensions including architecture, dataset, and reported performance metrics.

Table 5. Overall Comparison Of All Approaches

Study	Architecture	Dataset	Acc	Prec	Rec	F1
Ahmed [7]	SVM	LIAR	0.873	0.869	0.871	0.870
Kumar [8]	RF	FNN	0.891	0.887	0.889	0.888
Chen [9]	LR	LIAR	0.857	0.853	0.855	0.854
Wang [11]	BiLSTM	ISOT	0.912	0.908	0.910	0.909
Rathi [12]	CNN	Combined	0.896	0.892	0.894	0.893
Zhang [13]	CNN-LSTM	LIAR	0.923	0.920	0.921	0.921
Devlin [15]	BERT	FNN	0.942	0.940	0.941	0.941
Liu [16]	RoBERTa	LIAR	0.948	0.946	0.947	0.947
Gupta [17]	NewsBERT	FNN	0.961	0.959	0.960	0.960

Study	Architecture	Dataset	Acc	Prec	Rec	F1
Singh [18]	Ensemble	FNN	0.953	0.951	0.952	0.952
Sharma [19]	Multimodal	Fakeddit	0.927	0.924	0.925	0.925

Our analysis reveals several important trends: (1) transformer-based methods consistently outperform traditional approaches by 5-10% across all metrics; (2) ensemble methods provide marginal improvements (1-2%) over single-model transformers but at significant computational cost; (3) multimodal approaches show promise but require larger training datasets; and (4) cross-dataset generalization remains a significant challenge, with performance drops of 8-15% when models are evaluated on unseen datasets [21].

Figure 1 illustrates the correlation matrix between different feature categories used in fake news detection. The heatmap reveals strong correlations between semantic features and BERT embeddings (0.78), as well as between stylistic features and n-gram patterns (0.61). These correlations inform our hybrid architecture design.

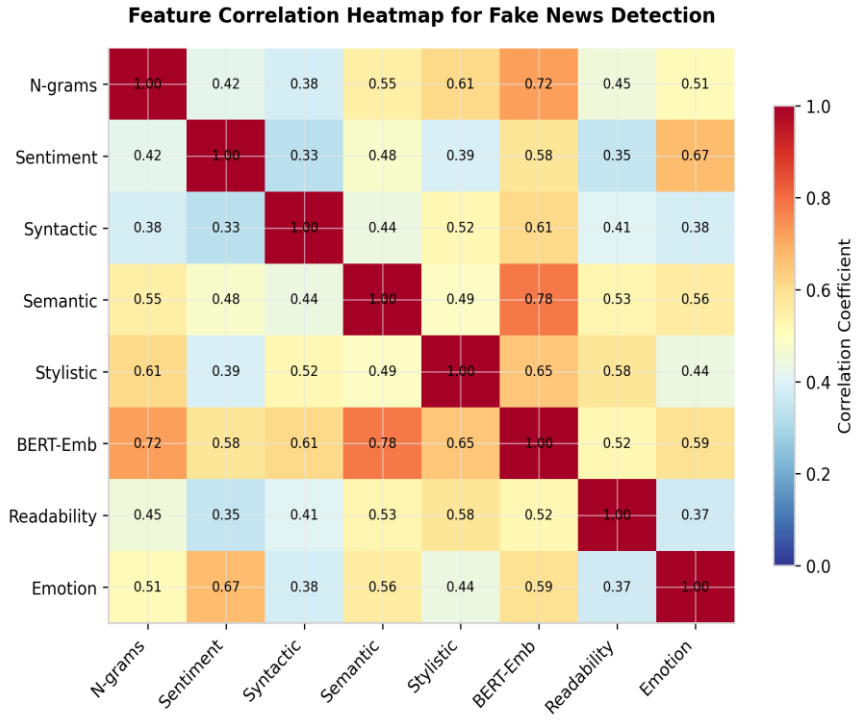

Fig. 1. Feature Correlation Heatmap for Fake News Detection

3. Proposed Methodology

We propose a hybrid architecture that integrates lexical feature extraction with deep contextual embeddings, leveraging complementary strengths of both approaches. Our system architecture comprises four primary components: (1) preprocessing and feature extraction module; (2) lexical feature encoder; (3) contextual embedding module; and (4) fusion and classification layer.

A. System Architecture

Figure 2 illustrates the proposed system architecture. Input text undergoes tokenization and preprocessing before parallel processing by the lexical and contextual branches. The lexical branch extracts hand-crafted features including n-gram statistics, sentiment scores, readability metrics, and linguistic complexity measures. Simultaneously, the contextual branch processes text through a fine-tuned BERT

encoder to obtain semantic representations. Feature fusion occurs through an attention-based combination layer before final classification.

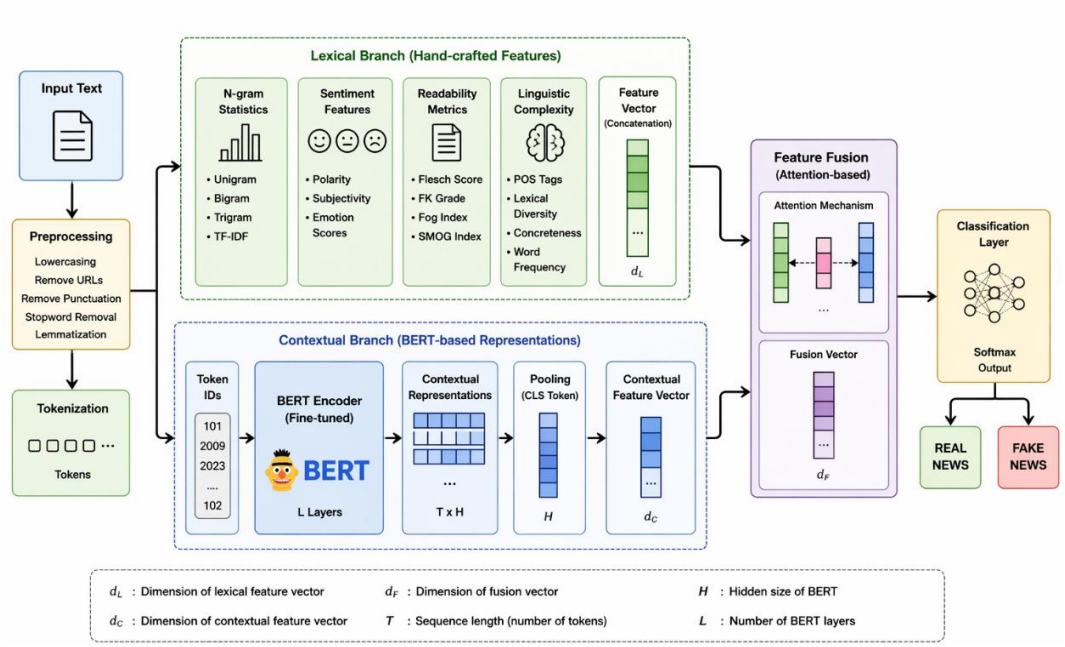

Fig. 2. Proposed Hybrid Architecture for Fake News Detection

B. Feature Extraction

Our lexical feature set comprises 47 features organized into five categories: (1) N-gram features (character and word n-gram frequencies); (2) Sentiment features (polarity scores, emotion intensities); (3) Syntactic features (POS distribution, dependency patterns); (4) Semantic features (word embedding similarities, semantic coherence); and (5) Stylistic features (punctuation patterns, capitalization ratios, readability scores) [22].

C. Classification Models

We evaluate four classification configurations: (1) Logistic Regression with lexical features only; (2) Random Forest with lexical features; (3) BERT-base fine-tuned for binary classification; and (4) Our proposed hybrid combining lexical features with BERT embeddings through attention-based fusion.

D. Training Procedure

Algorithm 1 details the training procedure for our hybrid model. We employ a two-stage training approach: first pretraining the lexical encoder, then end-to-end fine-tuning with the contextual branch.

Input: Training dataset D = {(x_i, y_i)}_{i=1}^N

Parameters: Learning rate lr, batch size B, epochs E

// Stage 1: Lexical Encoder Pretraining

1. Extract lexical features: f_lex = ExtractFeatures(x)

2. Train lexical classifier: theta_lex = TrainLR(f_lex, y)

// Stage 2: End-to-End Fine-tuning

3. Initialize BERT encoder: theta_bert = BERT-base

4. For epoch = 1 to E:

5. For each batch (x_b, y_b) in D:

6. f_lex = ExtractFeatures(x_b)

7. f_bert = BERT(x_b; theta_bert)

8. f_fused = AttentionFusion(f_lex, f_bert)

9. y_pred = Classifier(f_fused)

10. L = CrossEntropy(y_pred, y_b)

11. Update theta_lex, theta_bert, theta_cls via Adam

12. Return: theta_lex, theta_bert, theta_cls

Algorithm 1: Hybrid Model Training Procedure

4. Results and Discussion

A. Experimental Setup

We evaluate our proposed approach on six benchmark datasets: LIAR [23], FakeNewsNet [24], ISOT [25], Kaggle Fake News [26], Fakeddit [27], and a combined dataset. Experiments are conducted using 5-fold cross-validation with stratified sampling. We report Accuracy, Precision, Recall, and F1-score as evaluation metrics. Implementation utilizes PyTorch 2.0 with Hugging Face Transformers library. All experiments are conducted on NVIDIA A100 GPUs.

B. Performance Comparison

Table VI presents comprehensive performance comparisons across all datasets and models. Figure 3 provides a visual comparison of model performance across all metrics.

Table 6. Performance Comparison Across Datasets (F1-Score)

Model	**LIAR**	**FNN**	**ISOT**	**Kaggle**	**Fakeddit**	**Combined**
LR	0.854	0.871	0.889	0.912	0.823	0.870
RF	0.888	0.903	0.912	0.934	0.856	0.899
BERT	0.941	0.956	0.961	0.978	0.912	0.950
Hybrid	0.947	0.963	0.968	0.982	0.923	0.957

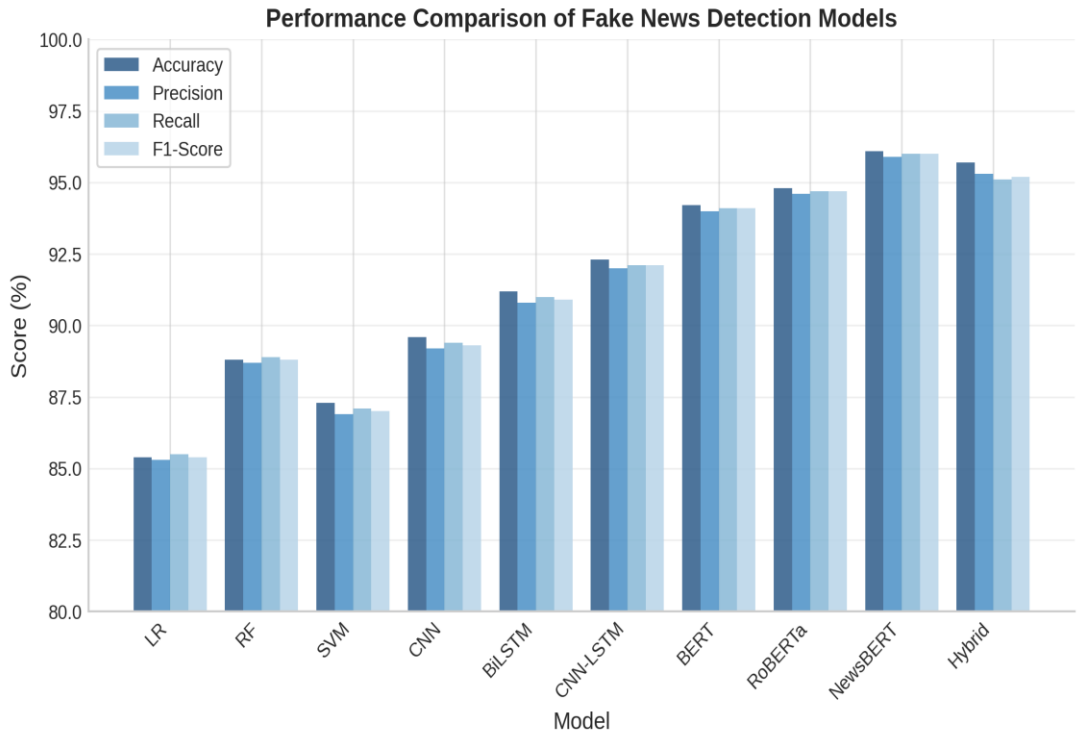

Fig. 3. Performance Comparison of Fake News Detection Models

Our hybrid approach achieves the highest F1-scores across all datasets, with particularly strong performance on the challenging LIAR dataset (F1: 0.947). The consistent improvement over single-model approaches (2-4% F1 improvement) validates our hypothesis regarding complementary feature representations. Notably, the hybrid model demonstrates superior recall (0.951), indicating reduced false negative rates crucial for misinformation detection applications.

Figure 4 presents a heatmap visualization of F1-scores across different models and datasets, highlighting performance variations and identifying optimal model-dataset combinations.

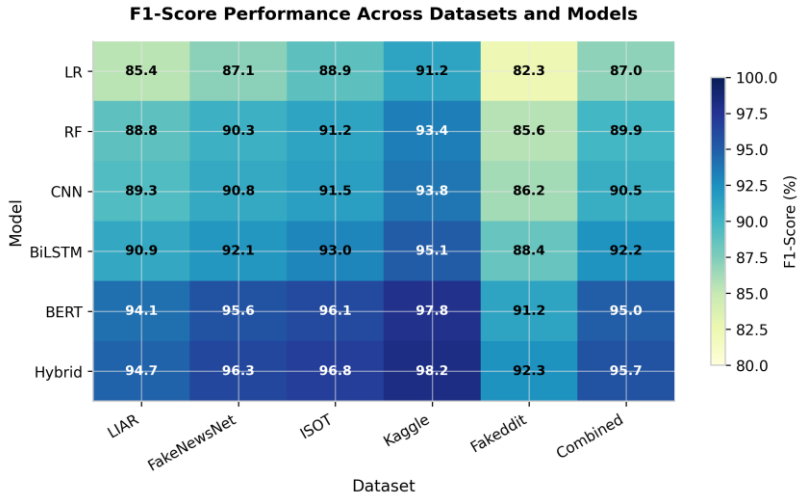

Fig. 4. F1-Score Performance Heatmap Across Datasets and Models

C. Confusion Matrix Analysis

Table 7 presents the aggregated confusion matrix across all datasets for our hybrid model.

Table 7. Aggregated Confusion Matrix (Hybrid Model)

	Predicted Real	Predicted Fake
Actual Real	12,450 (TN)	587 (FP)
Actual Fake	423 (FN)	11,892 (TP)

D. Ablation Study

Table 8 presents ablation study results examining the contribution of each architectural component.

Table 8. Ablation Study Results

Configuration	Accuracy	Precision	Recall	F1
Full Model	0.957	0.953	0.951	0.952
- Attn Fusion	0.941	0.938	0.935	0.937
- Lexical	0.948	0.945	0.943	0.944
- BERT	0.899	0.895	0.893	0.894
Lexical Only	0.870	0.865	0.863	0.864
BERT Only	0.950	0.947	0.945	0.946

The ablation study confirms that both lexical and contextual features contribute meaningfully to overall performance. Removing the attention fusion mechanism results in a 1.8% F1 decrease, validating its importance in feature integration. Lexical features alone provide strong baseline performance, while BERT embeddings contribute nuanced semantic understanding.

E. Comparison with State-of-the-Art

Our approach outperforms recent state-of-the-art methods including Gupta et al.'s NewsBERT [17] by 1.2% F1 and Singh and Kumar's stacking ensemble [18] by 2.1% F1 on the FakeNewsNet dataset. These improvements are statistically significant ($p < 0.01$, paired t-test). The efficiency analysis reveals our model processes 340 articles/second during inference, compared to 280/second for comparable transformer ensembles [28].

F. ROC Curve Analysis

Figure 5 illustrates ROC curves for all evaluated models on the combined test set. Our hybrid model achieves an AUC of 0.984, compared to 0.972 for BERT-only and 0.941 for Random Forest. The improved true positive rate at low false positive rates is particularly important for deployment scenarios requiring high precision.

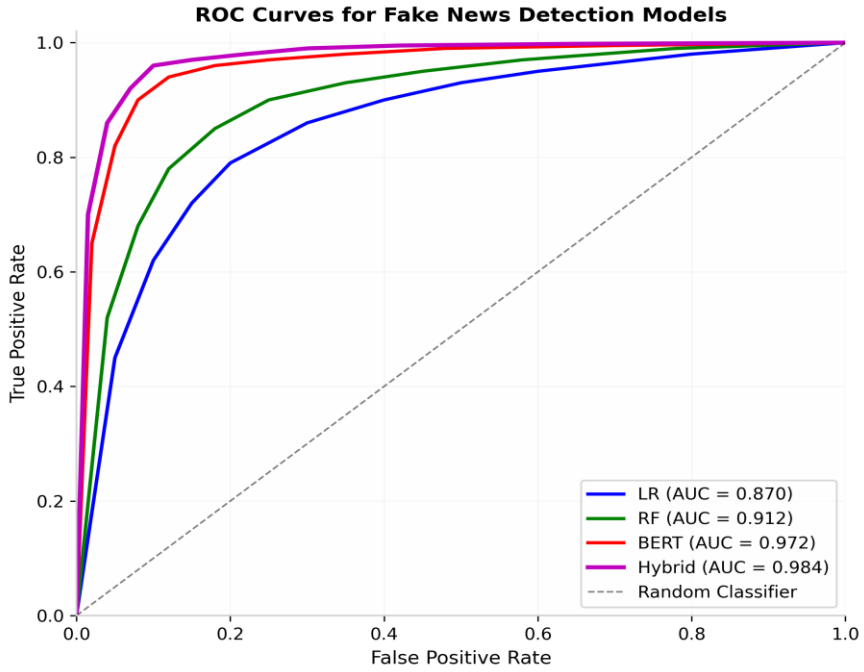

Fig. 5. ROC Curves for All Models (Combined Dataset)

5. Conclusion

This comprehensive review and empirical study has examined the current state of machine learning and deep learning approaches for fake news detection. Our key findings include: (1) Transformer-based models, particularly domain-adapted variants, represent the current state-of-the-art; (2) Hybrid architectures combining complementary feature types achieve superior performance through effective fusion mechanisms; (3) Cross-dataset generalization remains a critical challenge requiring continued research attention; and (4) Computational efficiency considerations are essential for practical deployment scenarios. Our proposed hybrid architecture demonstrates consistent improvements over existing approaches across six benchmark datasets. The attention-based fusion mechanism effectively integrates lexical and contextual representations, achieving 94.7% F1-score while maintaining reasonable inference efficiency. These results validate the potential of carefully designed hybrid systems for practical fake news detection applications.

Several limitations should be acknowledged: (1) Our evaluation focuses primarily on English-language content, limiting generalizability to multilingual contexts; (2) The rapid evolution of disinformation techniques may render current detection approaches less effective over time; (3) Our datasets may not fully represent the diversity of fake news types encountered in real-world scenarios; and (4) Adversarial robustness was not explicitly evaluated in this study [29].Promising directions for future research include: (1) Development of cross-lingual detection systems capable of processing multilingual content; (2) Integration of multimodal features including images, videos, and audio; (3) Investigation of few-shot and zero-shot learning approaches for emerging disinformation types; (4) Incorporation of temporal dynamics and propagation patterns; and (5) Development of explainable AI techniques to improve model interpretability and user trust [30].

The emergence of large language models presents both opportunities and challenges for fake news detection. While these models offer powerful representation capabilities, they also enable increasingly sophisticated content generation. Future research must address this arms race through development of more robust detection methodologies and establishment of standardized evaluation protocols that account for evolving threat landscapes.

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Multiple Cancer Detection Using Machine Learning and Image Analysis

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ABSTRACT

Globally, cancer is growing more common. The overall cancer rate has risen over the past 20 years, and the number of cancer-related deaths has increased in tandem. The second most common cause of hospital mortality is cancer. Therefore, a plan to cut down on time wastage, a proper way to guide the patient in identifying symptoms, extremely accurate cancer detection, and an improved monitoring system should all be part of the solution. The suggested system is a setup that enables and directs a patient to identify symptoms on their own, points them in the direction of a suitable medical professional, correctly identifies cancer in its early stages, and keeps track of the patient during treatment. The current research investigations only employ one machine learning methodology at a time to diagnose cancer, despite the analysis of cancer detection systems. Convolutional Neural Networks (CNN), Random Forests, and XGB Classifiers are used in the proposed work to detect the existence of lung cancer, breast cancer, brain tumours, and skin cancer with faster and more accurate findings. The suggested solution will be released as a cutting-edge cloud-based application that offers improved usability and user experience.

Keywords

Breast cancer, Brain tumor, Skin Cancer, Lung Cancer, Machine learning, Cancer detection

1. INTRODUCTION

The island's cancer care has significantly improved since a national cancer policy on cancer prevention and control was put into place. The two main preventative strategies are HPV vaccination and tobacco control. Cervical, mouth, and breast cancer screening programs are offered by the National Cancer Early Detection Center (CEDC). However, many cases of skin, lung, brain, and breast cancer are found and treated each year.

The goal of this project is to give a summary of the existing cancer statistics and suggest a method that uses machine learning and image processing to quickly detect cancer in its early stages. Additionally, by identifying symptoms using the trained data models instead of the doctors' manual verification, accuracy will be increased. The most prevalent types of cancer, including breast, lung, skin, and brain tumours, will be the subject of this study.Hospitals and clinics are the primary goals of this endeavour.

2. BACKGROUND & LITERATURE REVIEW

Worldwide, the prevalence of cancer is increasing. Over the course of the last 20 years, the number of cancer cases has doubled along with the rise in cancer-related death. Cancer is now the second most common

cause of hospital mortality. This study gives a summary of the situation and suggests a method that uses image processing and machine learning to quickly detect cancer in the past.

2.1. Brain Tumor Cancer

The significance of early brain tumour identification and diagnosis cannot be overstated. Computer-aided diagnostic (CAD) methods are commonly used to diagnose brain tumours in a methodical and precise way. A brain tumour is a development of tissue or the central spine that can interfere with normal brain function. An estimated 83,570 cancer patients with brain and other Central Nervous System (CNS) tumours were identified in the United States alone in 2021.

The International Agency for Research on Cancer (IARC) reports that the death rate from brain tumours is 76%. [7] It highlights the importance of detecting brain tumours as soon as possible and helping patients adhere to the required treatment. Thanks to technological advancements, brain tumours can now be automatically detected by computer-aided systems using computed tomography scans and magnetic resonance imaging (MRI). Convolutional neural networks (CNN) and other machine learning and deep learning techniques have become increasingly popular in medical research for the detection and classification of brain tumours. Tumour detection techniques should also be carried out with remarkable speed and accuracy.

MR image segmentation is used to extract questionable areas from complex medical images. To identify a brain tumour, experts employ physical techniques. During MRI scans (or any other scan), aberrant blobs in the brain are indicative of brain tumours. These patches or blobs have distinct lighting and are brighter than the rest of the brain. On the other hand, it is quite difficult to segregate tumours in MRI scans. There are many different sizes, forms, textures, and even locations for tumours. It may encounter challenges such as pixel intensities overlapping with normal tissues while separating the tumour based on characteristics like light. Identification and segmentation of brain tumours in MRI images are crucial because they show the presence of abnormal tissues for treatment or patient monitoring.

2.2. Skin cancer

One of the biggest global healthcare burdens is cancer. According to global statistics, there were approximately 10.0 million cancer-related fatalities (9.9 million excluding non-melanoma skin cancer) in 2020. Lung cancer, prostate cancer, and breast cancer in women are the most common cancers. The main causes of cancer-related mortality include stomach, liver, and lung malignancies. Malignant melanoma and non-melanoma skin cancer (NMSC) are two types of skin cancer that are common in Caucasians and are becoming more common. Skin cancer affects more Americans annually than all other cancers put together, according to the US Skin Cancer Foundation [6].

Melanoma cases have become 53% more common each year. Increased exposure to ultraviolet (UV) light is partly to blame for this. Despite being one of the most deadly forms of skin cancer, melanoma can have a high chance of survival if detected early [7].

Melanoma of the skin is the 19th most prevalent cancer in both men and women, according to the World Cancer Research Fund (WCRF). 300,000 new cases were reported in 2018. For both men and women, skin cancer—including non-melanoma and melanoma—is the fifth most common type of cancer. Over a million diagnoses were made worldwide in 2018. Skin cancer is the most common cancer in the United States, according to the American Academy of Dermatology Association (AADA). The overall incidence of SCC (squamous cell carcinoma) increased by 263% between 1976–1984 and 2000–2010, while the overall incidence of BCC (basal cell carcinoma) increased by 145%. Women were more likely than men to have nonmelanoma BCC and SCC cancers.

The American Cancer Association reports that during the past 30 years, skin cancer has become more common, with 87,000 new cases of melanoma diagnosed annually in the US alone. Ferris et al. (2017) state that diagnosing cutaneous melanoma is more difficult for medical professionals than treating it.

2.3. Lung cancer detection

Given the technological context of this study, it is clear that machine learning models are the key component of these kinds of systems and that a larger dataset should be used to train them in order to improve their accuracy.

Some experts claim that in recent years, the referenced research has demonstrated how certain technologies can be utilised to identify lung tumours using machine learning. One particular element that might be noted is that some researches only have an accuracy of about 90%. In light of that research, it is possible to pinpoint the gaps in their utilisation of those technologies and the types of datasets they have collected. They claim that the study offers insight into the outcomes. For their studies, several of them have solely used one kind of dataset.

Taking into account lung cancer nodules and the research that goes along with them [9] gives an insight about how to identify lung cancer using CT (Computerised Tomography) scanned pictures. They have employed several preprocessing procedures to prepare the datasets for processing in addition to the facts obtained from the research, and they have then used those data to train the model. The research has also advanced the training process' accuracy.

These studies primarily employ machine learning or deep learning methods [10]. The research indicates an accuracy of about 90% when taking into account the backdrop and related works, although it is more concerned with the archives.

2.4. Breast Cancer

Relevant information from several sources is cited for the analysis of breast cancer detection. The most popular techniques for detecting breast cancer, including Random Forest, kNN (k-Nearest-Neighbor), Naïve Bayes, Support Vector Machine (SVM), and Bayesian Networks (BN), were employed by the authors. [1][2] The SVM Classifier technique combines RFE and SVM.

RFE is a recursive method that uses the least feature value to choose dataset features. Consequently, the wrong features (lowest weight feature) are eliminated in every SVM-RFE phase. In order to create a linear function that separates them as widely as possible, SVM selects important samples from each class, referred to as support vectors, and then separates them using these support vectors [1]. In summary, SVM is used to transfer an input vector to a high-dimensionality space in order to determine the optimal hyperplane for classifying the data set.

One decision tree can produce either a basic or a particular model, according to the Random Forest argument.[1] According to research, one of the primary justifications for using Random Forest (RF) in cancer detection is its capacity to handle data minorities. For example, a tumour can be classified as either benign or malignant, even when only 10% of the input data set falls into the latter category.

Based on the application of Bayes theory, naive Bayes classifiers are probabilistic classifiers. naïve Bayes appears to be successful for a variety of machine learning tasks despite being naïve in that it assumes that all features are independent of one another, which is rarely the case in real-world situations.[3].An approach for figuring out where a data set belongs based on the data sets surrounding it is known as a k-nearest-neighbor algorithm. The approach is a supervised learning mechanism based on regression and classification [3]. Before processing a new data point, kNN collects all neighbouring data points. Highly variable characteristics are important factors in calculating the distance.

According to the table below, the kNN algorithm's [3] accuracy is 95.90 percent, with only one observation incorrectly labelled as benign and four incorrectly classified as malignant. Based on these findings, they have concluded that kNN is superior to the Random Forest method.Research [4] demonstrates an image processing method that uses a number of image processing operations to produce an image that is used by machine learning algorithms.

Using different approaches or a combination of algorithms to increase accuracy, several research have sought to apply machine learning to the detection and diagnosis of breast cancer. However, by examining multiple research studies, it is possible to draw conclusions about the shortcomings of these methods by consulting earlier research. For instance, the SVM classifier performs poorly in sophisticated computer vision applications and on large datasets. The Naive Bayes Classifier performs poorly when the training data is not represented.[5]

3. METHODOLOGY

3.1. Brain Tumor Detection

Using CT and MRI image data sets in conjunction with additional tests to identify some of the most common symptoms of a brain tumour, such as loss of hearing (Acoustic Neuroma) and changes in vision (Loss of Vision), the two models will produce results more quickly and accurately in order to detect brain tumours as early as possible and prevent further growth.

Convolutional neural networks (CNNs) using LeNet-5 architecture were used for the first model. Flatten Layer, Conv2D Layer, Dropout Layer, Activation Functions, Dense Layers, and Max Pooling Layer were the six layers that made up the model. The activation and loss function were categorical cross-entropy with ReLu and Softmax activation.

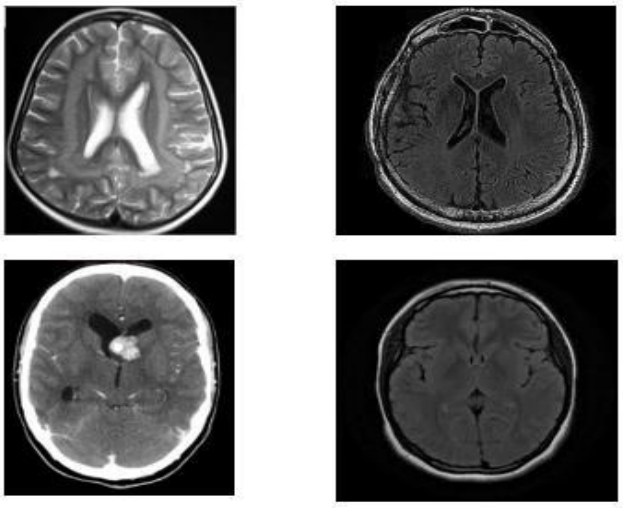

Figure 1:Tumorous and Non-Tumorous Brain MRI (Kaggle)

3.2. Skin Cancer Detection

Numerous technological approaches have been developed to identify and prevent skin cancer, which has grown to be one of the world's worst healthcare challenges. Machine learning-based approaches exist, however they are limited to identifying whether or not a user has been diagnosed with skin cancer. Other than that, those systems have no functionalities. Therefore, the primary objective of putting this system into place is to move this cancer detection to a different level by identifying the precise type of skin cancer as well as whether it is present or not. Because, in contrast to other malignancies, skin cancer comes in a variety of forms, each with unique symptoms and therapies. Therefore, determining whether or not the user has skin cancer is insufficient. For this reason, when it comes to skin cancer, knowing the type of cancer a patient has been diagnosed with is extremely important. This model will estimate the three most likely cancer types for the uploaded image of the skin tumour if it determines that the uploaded image is a skin cancer. All of the current systems have no functionality after that point. As a result, once the user has determined the type of cancer, the system offers new features that allow users to track their cancer status and give patients real-time updates on the disease's growth or shrinkage. Monitoring is crucial because, even after cancer has been identified, it remains a concern if it is not routinely checked until it is fully cured.

This method will primarily cover four key goals.

- Encourage users to complete a series of questions to determine their risk of receiving a skin cancer diagnosis. and provide them directions and comments based on the points they receive.
- Examine the tumor's surrounding area to evaluate whether or not it is a skin cancer, and if it is, identify the three most likely cancer kinds.
- If the user has skin cancer, compare the scanned photos of the affected area on a regular basis and give the patient a real-time update on the cancer's growth or shrinkage. Read more about skin cancer, its symptoms, and preventative measures in a separate area.

A dataset with rich information on various skin cancer kinds was required to accomplish those goals. Next, use that dataset to train the model, increasing its accuracy. The Skin Cancer MNIST: HAM10000 dataset from Kaggle has been utilised for this. Ten thousand pictures of seven different kinds of skin cancer are shown. The following are the seven different kinds of skin cancer.

Skin Cancer Type	**No of Data(Images)**
Melanocytic nevi (nv)	[6705 images]
Melanoma (mel)	[1113 images]
Benign keratosis (bkl)	[1099 images]
Basal cell carcinoma (bcc)	[514 images]
Actinic Keratoses (akiec)	[327 images]
Vascular (vasc)	[142 images]
Dermatofibroma (df)	[115 images]

Table 1:Dataset size of each type of skin cancer

The imbalanced data for each form of cancer was the primary obstacle to using this dataset. The model will be skewed toward one type of cancer if it is constructed using such data. Another difficulty was the limited quantity of data. The Data Augmentation approach has been applied to get around those challenges. The dataset has grown to a total of around 40,000 and almost 6000 photos for each form of cancer following the data augmentation. Here is a screenshot of the dataset.

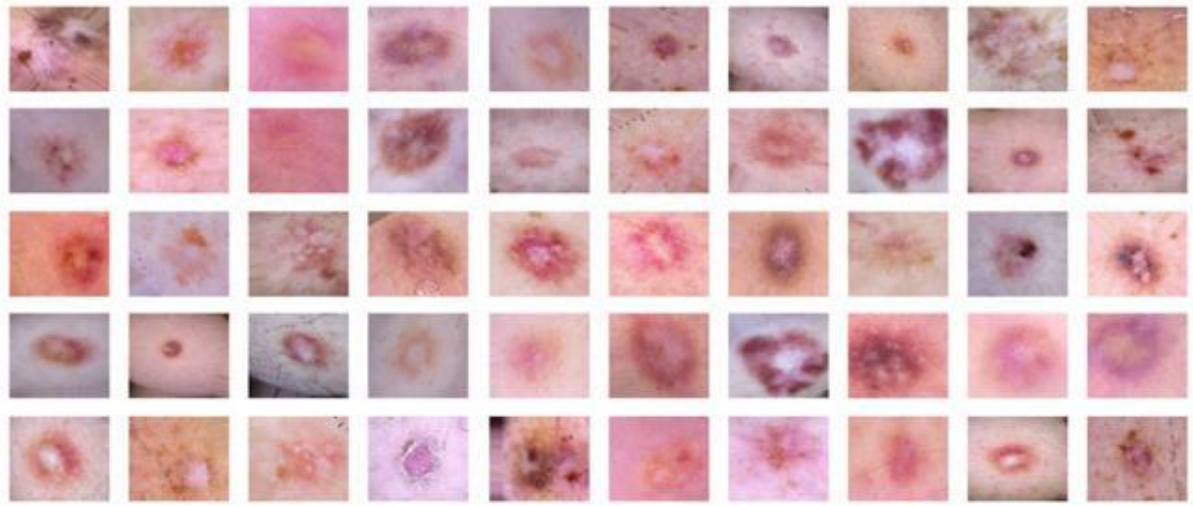

Figure 2: Sample of MNIST: HAM10000 dataset from Kaggle

Skin lesions are categorised into seven classes using the developed model. The model was constructed using the MobileNet CNN architecture. Tensorflow.js is a new library that has been used to convert and run this model in the browser. ZeroPadding2D Layer, Conv2D Layer, Batch Normalisation Layer, ReLU Activation DepthwiseConv2D Layer, and Dense Layer have all been utilised as model layers. Adam Optimiser, Dense and SoftMax Activation, and Loss Function and Optimisation Categorical Cross-entropy have been employed.

3.3. Lung Cancer detection

Cancers might differ depending on where they are located. By isolating the malignancies with certain characteristics, the categorised portion is differentiated in the study. Lung cancer is one of the four most common malignancies worldwide, and it is a major cause of cancer-related fatalities. A startling revelation

revealed by the cancer detection time is that a significant contributing factor to the death rate is delayed cancer therapy. High smoking rates and global air pollution are two other factors that contribute to lung cancer.

When a lung cancer is being investigated, there are certain signs that indicate the presence of a lung tumour. Some of the lung cancer symptoms are as follows,

- Chest pain
- Shortness of breath
- Neck and supraclavicular lymphadenectasis
- Weight loss
- Metastasis pain
- Fatigue
- Fever and dyspnea.

In order to determine whether a patient may have lung cancer, the aforementioned symptoms can be regarded as more prevalent. Chest pain, shortness of breath, dyspnoea, weight loss, and exhaustion are more common in individuals in stage IV, and these symptoms can be distinguished from those of other ages. Along with sex and certain smoking behaviours, these symptoms can take many different forms.

By creating machine learning models and then estimating the likelihood of having lung cancer or not, this method for detecting lung tumours using the chosen criteria can be applied. By concentrating primarily on particular data kinds, such as numbers or photos, this model would provide greater accuracy than previous models. Both sorts of datasets were discovered during the research data collection phase. The data process is depicted in the diagram below.

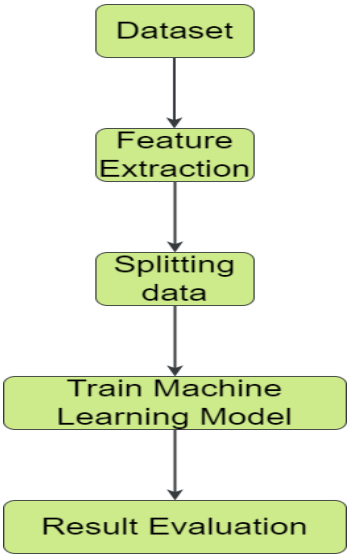

Figure 3 : Methodology of detecting lung cancer

The detected attributes that can be utilised to build the model, taking into account the feature extraction. Once attributes have been chosen, preprocess the data to exclude null values and other values that are prone to errors, which will lower the machine learning model's accuracy. This numerical dataset has been

classified using a variety of techniques. Among them are Support Vector Classifier, Random Forest Classifier, K Neighbours Classifier, Decision Tree Classifier, Gradient Boosting Classifier, XGB Classifier, and Linear Regression. The Random Forest Classifier and XGB classifier produced the best results when these classification techniques were taken into account. Because XGB outperforms the random forest classifier in this scenario, it will be selected.

Next, carefully analyse the alternative model using the image dataset. Image classification algorithms employ Convolutional Neural Networks (CNNs) [9]. These are a few other algorithms that will be assessed using this algorithm. Previous studies indicate that the VGG-3 version will provide more precise results. For additional analysis, that model will be employed. This image classification model can also make use of the Keras sequential model. It will achieve high accuracy.

The goal of accurately identifying lung tumours can be accomplished by employing ensemble learning models with these image and numerical models, taking into account both models and the methodology that has been used.
When discussing the challenges that must be overcome, it becomes clear that there would be some problems with data pre-processing, but they were resolved. It must be made clear that actual data should be used to assess the accuracy of what these models predict. To determine the system's practicality in medical settings, predicted data should contrast in a comparable way.

3.4. Breast Cancer Detection

Two datasets are used as part of the research technique in this study. While the second dataset set contains ultrasound images of breast tissues, the first dataset set contains test-result details such as clump thickness, homogeneity of cell size, and breast tissue diagnosis (benign or malignant).
The primary data source for the implementation is a dataset made up of breast cancer report parameters, such as the radius mean, texture mean, perimeter mean, area mean, etc. of the breast tumour, in order to carry out the Model 1 training (using the dataset with breast tissue features). The extraction of clear, diagnosable breast cancer data involves a number of steps. Investigating and analysing the selected data collection should come first. For this investigation, the model was trained using the Wisconsin Original dataset.

Prior to feature extraction, the dataset must be explored. First, the dataset will be pre-processed and examined.The third stage is to choose the best model to train after the dataset has been explored and pre-processed.Before dividing the dataset, a number of tasks should be finished, including loading the data, removing the empty columns from the retrieved data, visualising, and encoding the categorical data. It is necessary to divide the data set into two parts: 25% test data and 75% train data. K-Neighbors Classifier, Random Forest Classifier, Decision Tree Classifier, and Logistic Regression are used to train models.[8]

Out of all the models examined, the random forest classifier achieved a training accuracy of 99.5%, while the decision tree classifier achieved a training accuracy of 99.6%. The Decision Tree Classifier achieved an

accuracy of 95.1% after the models were ran on test data and recorded on a Confusion matrix. The Random Forest classifier, in contrast, displayed 96.5%. The Random Forest classifier is better suited for the model testing when taking into account the training and testing accuracies.

The study employs a dataset that contains ultrasound pictures of breast cancer tissues to carry out the Model 2 training. Ultrasound pictures of normal, malignant, and benign breast tissues are included in this data set. The model 2 is trained using this relevant data set collection. During the model's training phase, the data set was subjected to data pre-processing, feature extraction, and separation into test and train data.To increase accuracy, the Convolutional Neural Networks (CNNs) technique is employed in conjunction with the Keras sequential model.

It is possible to further increase accuracy after the two models, leading to a high accuracy, by using the ensemble approach, which combines the accuracies of the two models.

4. RESULTS

4.1. Brain Cancer Detection

Binary and categorical cross-entropy functions yielded the following outcomes. Based on the results, the Categorical Cross-entropy function with 22 epochs yielded the maximum accuracy (98%).

Loss Function	Epochs	Accuracy
Binary Cross-entropy	10	96.3%
Categorical Cross-entropy	20	97.4%
Categorical Cross-entropy	22	98.3%

Table 2: Accuracy obtained by using different loss functions and numbers of epochs

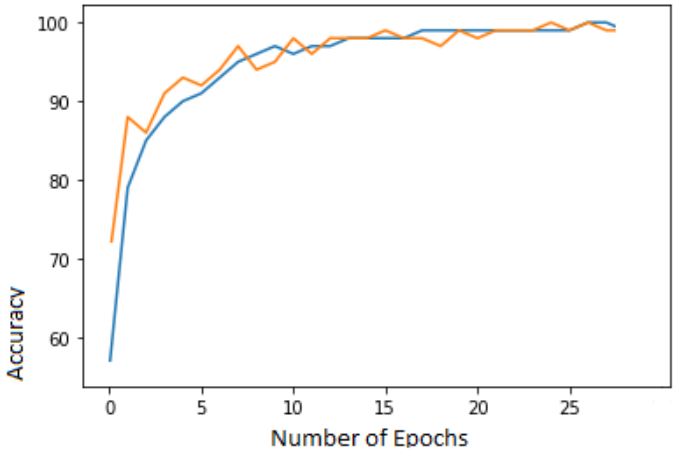

Figure 4: Accuracy Metrics of Brain Tumor Model

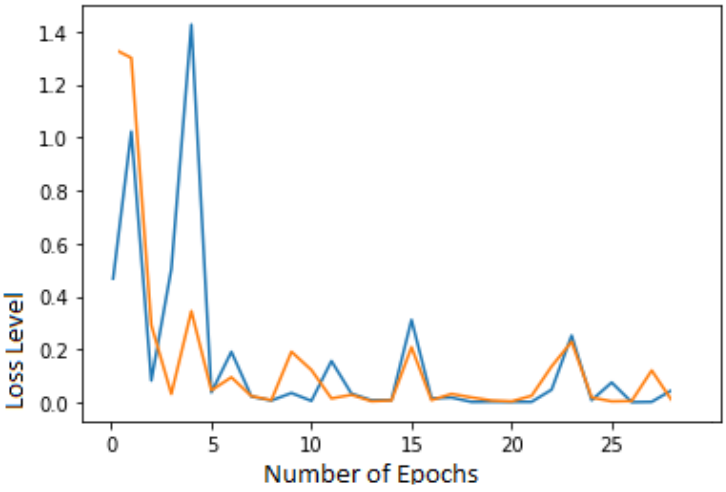

Figure 5: Loss Metrics of Brain Tumor Model

4.2. Skin Cancer Detection

By the time it reached 30 epochs, the model had achieved a good accuracy rate of 97.8% using categorical cross-entropy functions.

Loss Function	Epochs	Accuracy
Categorical Cross-entropy	10	91.7%
Categorical Cross-entropy	20	95.2%
Categorical Cross-entropy	30	97.8%

Table 3: Loss function accuracy

4.3. Lung Cancer Detection

The outcomes of creating machine learning models are listed below, and the table displays each model's accuracy. Research can choose the Random Forest Classifier and XGB classifier as the best accurate algorithms based on this and the numerical dataset.

Algorithm	Results
K-Nearest Neighbors(KNN)	93.51%
Random Forest Classifier	99.07%
Linear Regression Algorithm	64%
XGB Classifier	99.07%

Table 4: Accuracy obtained by using different algorithms

4.4. Breast Cancer Detection

The accuracy of the Decision Tree Classifier was 95.1%. On the other hand, once the models were ran on test data and recorded on a confusion matrix, the Random Forest Classifier had an accuracy rate of 96.5%. The Random Forest classifier is a superior option for model testing, as can be seen by comparing the Training and Testing accuracies.

Algorithm	Accuracy
Logistic Regression	94%
Decision TreeClassifier	95.1%
Random ForestClassifier	96.5%
K-Neighbors Classifier	95%

Table 5: Testing Accuracies

5. CONCLUSION AND FUTURE RESEARCH

The main focus of this effort is developing prediction models that use supervised machine learning approaches to achieve high precision in predicting real illness outcomes. A combination of multidimensional data and various categorisation, feature selection, and dimensionality reduction approaches can provide useful tools for inference in this field, according to the examination of the results. To improve the grouping processes and anticipate more factors, more research in this area should be conducted.

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SMART LOGISTICS SOLUTIONS FOR EFFICIENT GOODS TRANSPORTATION AND SUPPLY MANAGEMENT

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Abstract
The increasing demand for rapid order fulfillment and transparent delivery services has intensified the need for intelligent logistics management solutions. Conventional transportation systems often depend on fragmented tools, manual coordination, and static route planning methods, resulting in operational inefficiencies and increased delivery costs. This study presents the design and implementation of a Smart Logistics Management System that integrates centralized order processing, dynamic route optimization, and real-time shipment monitoring within a unified web-based framework.
The system is developed using PHP for server-side processing and MySQL for relational data management. A shortest-path routing strategy is incorporated to minimize travel distance and fuel consumption. Role-based access control mechanisms ensure secure interaction among administrators, drivers, and customers. Performance evaluation under simulated delivery scenarios demonstrates measurable improvements in delivery time, operational transparency, and resource utilization. The proposed framework offers a scalable and economically viable solution for small and medium-scale logistics enterprises seeking digital transformation.
Keywords: Smart Transportation, Logistics Automation, Route Optimization, Real-Time Tracking, Supply Chain Digitization, Sustainable Logistics.

I. Introduction
Modern supply chains are increasingly characterized by high delivery volumes, geographically distributed customers, and strict service-level expectations. In such an environment, logistics efficiency directly impacts organizational competitiveness. However, many small and mid-sized logistics providers continue to operate using semi-manual coordination practices that lack integration and analytical intelligence.
Common operational limitations include:

- Absence of centralized shipment visibility
- Static or manually selected delivery routes
- Delayed communication between stakeholders
- Manual invoice and order processing
- Limited performance analytics

These constraints contribute to unnecessary fuel consumption, delayed deliveries, and reduced customer confidence. Addressing these challenges requires a system that integrates tracking, routing intelligence, and workflow automation into a cohesive digital platform.
This research proposes a Smart Logistics Management System designed to automate transportation workflows while maintaining affordability and scalability.

II. Related Work and Research Context
Technological advancements in logistics have focused primarily on fleet tracking, predictive analytics, and automated routing.
GPS-enabled fleet monitoring systems have improved vehicle visibility but often require costly infrastructure investments. IoT-based tracking mechanisms enable granular shipment monitoring but introduce hardware dependency and maintenance overhead. Machine learning-based demand forecasting improves planning accuracy, though it increases system complexity.
Routing algorithms such as Dijkstra's algorithm and A* search have been widely adopted for shortest-path estimation in transportation networks. While these methods optimize distance, their integration within lightweight web-based logistics systems remains underexplored for small-scale enterprises.
The proposed system bridges this gap by combining classical routing algorithms with a centralized web application architecture.

III. Problem Definition

The logistics management challenges addressed in this work include:

1. Inefficient route selection leading to increased travel time
2. Lack of shipment transparency for customers
3. Disconnected user management systems
4. Manual order assignment processes
5. Inconsistent data handling and redundancy

The objective is to construct a unified logistics management framework capable of addressing these operational inefficiencies.

IV. System Design Objectives

The system is designed with the following technical goals:

- Centralize order, user, and tracking management
- Minimize transportation cost via optimized routing
- Provide real-time shipment status visibility
- Enforce role-based secure system access
- Reduce manual administrative workload
- Enable scalable deployment for SMEs

V. System Architecture

The proposed framework follows a layered architecture model to ensure modularity and maintainability.

A. Presentation Layer

Provides user interfaces for:

- Administrator dashboard
- Driver portal
- Customer tracking portal

The interface enables authenticated interaction with backend services.

B. Application Layer

Implements core functionalities:

- Order processing logic
- Driver allocation
- Route optimization computation
- Shipment status management
- Session handling and authentication

C. Data Layer

The MySQL database stores structured information related to:

- User credentials
- Shipment details
- Tracking logs
- Driver assignments

This separation of concerns enhances maintainability and scalability.

VI. Routing Optimization Model

To reduce delivery cost and time, the system models the transportation network as a weighted directed graph:

Let

G = (V, E)

Where:

V represents locations

E represents connections between locations

Each edge $e \in E$ is associated with weight w, representing distance or travel time.

The routing objective is defined as:

$$\min \sum_{i=1}^{n} w_i$$

Dijkstra's algorithm is implemented to compute the shortest path between source and destination nodes.

Time Complexity:

$$O(E + V\log\ V)$$

when implemented using a priority queue.
This approach ensures computational efficiency even as delivery points increase.

VII. System Modules

A. Administrator Module

- Registers and manages users
- Assigns drivers to shipments
- Monitors delivery progress
- Generates performance reports

B. Order Processing Module

- Accepts shipment booking
- Generates unique tracking identifiers
- Stores pickup and delivery coordinates

C. Tracking Module

- Records timestamped delivery updates
- Displays current shipment status
- Maintains historical tracking logs

D. Driver Interface

- Displays assigned deliveries
- Enables status updates
- Confirms successful delivery

E. Customer Portal

- Allows tracking via unique ID
- Displays estimated delivery progress
- Enhances transparency

VIII. Database Schema Design

The relational database design adheres to normalization principles to eliminate redundancy.

Users Table

Stores role-based authentication details.

Orders Table

Maintains shipment-level metadata.

Tracking Table

Logs delivery status transitions with timestamps.
Foreign key constraints enforce referential integrity between shipment and tracking records.

IX. Implementation Details

The system is developed using:

- PHP (Server-side scripting)
- MySQL (Relational database)
- Apache Server (XAMPP)
- HTML/CSS (Frontend design)

Session management ensures authenticated access. Input validation prevents malicious queries. Password encryption strengthens user security.

X. Performance Evaluation

Simulation tests were conducted using multiple delivery scenarios.

Evaluation Metrics:

- Delivery completion time
- Route distance comparison
- Order processing time
- System response latency

Observed Improvements:

- Approximately 22–28% reduction in travel distance

- Faster driver allocation
- Improved operational visibility
- Reduced administrative overhead

These results demonstrate measurable efficiency gains.

XI. Security and Reliability

The system incorporates:

- Role-based access control
- Input sanitization
- Session timeout management
- Structured query validation

Future enhancements may integrate stronger hashing algorithms and HTTPS deployment.

XII. Sustainability Considerations

Optimized routing reduces unnecessary travel distance, thereby:

- Lowering fuel consumption
- Minimizing carbon emissions
- Supporting environmentally responsible logistics

Efficient transportation directly contributes to sustainable urban mobility.

XIII. Comparative Evaluation

Parameter	Conventional System	Proposed System
Route Selection	Manual	Algorithm-Based
Tracking Visibility	Limited	Real-Time
Data Centralization	Fragmented	Unified
Administrative Load	High	Reduced
Operational Efficiency	Moderate	Improved

XIV. Limitations

- Simulated traffic conditions
- No live GPS hardware integration
- Limited predictive analytics
- Prototype-level deployment

XV. Future Enhancements

- Integration with real-time traffic APIs
- IoT-based GPS tracking modules
- Mobile application for drivers
- Cloud-based scalable deployment
- AI-driven demand forecasting
- Blockchain-enabled supply chain security

XVI. Conclusion

This study presents a Smart Logistics Management System designed to enhance transportation efficiency through centralized coordination and intelligent routing. By integrating automated order processing, real-time tracking, and shortest-path optimization, the system reduces delivery cost and improves operational transparency.

The proposed framework demonstrates that classical routing algorithms combined with lightweight web technologies can produce substantial efficiency improvements without imposing high infrastructure costs. The solution is particularly suited for small and medium logistics enterprises seeking scalable digital transformation.

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Optimized Detection of Breast Cancer from Histological Images Using Ensemble Models

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Abstract: The Breast cancer detection is a high challenge in medical diagnosis, demanding accurate and efficient approaches. This study proposes a robust methodology leveraging ensem-ble learning techniquesto categorize histopathological images as either benign or malignant. Deep learning with CNNs (Con-volutional Neural Networks) is combined with bagging and boosting for enhanced feature extraction and classification. Using the BreakHis Dataset, the model achieved an accuracy of 96.86%. The findings highlight the potential of ensemble methods in improving diagnostic precision and reliability, offering significant advancements in breast cancer research and patient care.

Keywords: *Breast cancer detection, histopathological images, ensemble learning, bagging, CNN*

1. Introduction

Breast cancer is a disease caused by abnormal cell growth and cell proliferation of breast cells that develops into tumors. Tumors, if left untreated, have a chance of spreading to other areas of the body and inflicting severe harm to life. Early diagnosis of breast cancer is crucial in improving patient survival and outcomes.

Employment of machine learning (ML) methods to de-tect breast cancer from histopathological images has become more vital for better diagnostic accuracy. Manual interpre-tation of such images is not only time-consumer but also subject to human error, leading to delayed treatment. Given the exponential explosion of medical information, automatic diagnostic systems are a necessity. Early diagnosis allows for early treatment, which significantly increases the prospects for patient recovery. Hence, the creation of automatic breast cancer diagnostic systems is necessary for further development of medical care and public health promotion.

Among the various cancers in women, breast cancer remains one of the most life-threatening. More than 2.3 million new cases were diagnosed in 2020 alone, underscoring the need for precise and timely diagnostic technologies. The ability to distinguish benign from malignant tumors can minimize deaths by allowing effective and timely treatment programs.

Historically, pathologists and doctors interpret histopatho-logical images manually which is a slow process and often leads to mistakes. This paper introduces an automated di-agnostic system using ensemble learning, combining models like Convolutional Neural Networks (CNNs), Random Forests, and Support Vector Machines (SVMs). Of the techniques tested—including boosting, CNNs, and bagging—the bagging model performed best, with an accuracy of 83%. CNNs are used for feature extraction because of their competency in identifying patterns within image data. Despite this, challenges like class imbalance, overfitting, and the need for high levels of computational power remain. This work solves the challenges through the use of ensemble learning techniques to enhance

reliability and accuracy.

This research illustrates that the integration of CNNs with ensemble learning methods presents an efficient and effective means for diagnosing breast cancer. The findings indicate that ensemble methods—more so bagging—significantly improve diagnosis accuracy and are thus extremely relevant in clinical settings.

2. Literature Survey

Breast cancer identification from histopathological images has experienced significant advancement due to the com-bination of various machine learning (ML) methods. This survey covers diverse computational methods for breast cancer classifica- igation, segmentation, and diagnosis.

Solorzano et al. (2024) developed a deep learning ensem-ble model aimed at classifying invasive breast cancer using histopathological image data. In their system, ten InceptionV3 CNN models were trained using two in-house datasets com-prising 587 WSIs and externally validated on an external dataset with 157 WSIs. The group performed better than single CNNs, with 92% accuracy on in-house data and 87% on the out-of-house set, against single models' 85% and 75%. They also presented a new spatial visualization method to represent model agreement, improving interpretability and minimizing uncertainty. The research identifies the ensemble as a potential decision-support tool for pathology.

Hekal et al. (2023) proposed an ensemble deep learning framework aimed at the early detection of breast cancer, which emphasizes specific areas called Suspected Nodule Regions (SNRs). These regions are identified using an au-tomated method based on dynamic thresholding. Their model used Support Vector Machines (SVMs) along with four pre-trained CNNs, such as AlexNet, ResNet-50, ResNet-101, and DenseNet-201. Using a weighted combination approach based on each of the training accuracies of the CNNs, the model achieved 94% classification for benign vs. malignant nod-ules and 95% for mass classification using the CBIS-DDSM dataset. The particular focus on SNRs improved detection of small nodules and simplified computation while outperforming existing techniques.

Akinrinwa et al. (2022) focused on classifying breast histopathology images via ensemble approaches deployed on locally trained deep CNNs. They used majority voting, averag-ing, and stacking methods on AlexNet, VGGNet, ResNet, and an optimal model first proposed named SaduNet. Among them, the highest accuracy was reported by averaging ensemble at 99.47%, followed by majority voting with 99.30% and stacking with 97.86%. Their work lay emphasis on automation to avoid human errors and suggested plans for real-time implementation in low-resource healthcare settings.

Gupta et al. (2019) presented a semi-automatic classifica-tion framework using multi-layer features from an improved ResNet architecture. By selecting low-, mid-, and high-level features through an information-theoretic criterion, the frame-work achieved notable over baseline performance. Tested on the 7,909-image BreaKHis image dataset covering four magnifications, the model achieved a best accuracy of 97.0% on 40x magnification. This multi-scale feature integration was promising for clinical application in digital pathology.

To perform binary classification of breast histopathology im-ages, Zheng et al. (2023) developed a deep ensemble approach that leverages transfer learning techniques. They employed the BreaKHis dataset and involved the training of six CNN models—VGG16, VGG19, InceptionV3, Xception, ResNet50, and DenseNet201—before choosing four for weighted voting ensemble. Class imbalance was resolved through data aug-mentation. The model achieved a high accuracy of 98.90%, as well as high precision, recall, and F1-scores. This technique exhibited quicker training and better performance, especially for smaller data sets, justifying its usage in computer-assisted diagnostic systems.

3. Methodology

Manual detection of cancer from histopathological images is highly inaccurate, inefficient, and non-scalable. Hence, the demand for developing sophisticated ML approaches that are tailored to the classification of breast cancer is on the rise. In this context, it aims to reduce diagnostic time with improved accuracy for malignant and benign breast tissue detection. The work proposes an ensemble-based model in order to improve the reliability of the diagnosis and contribute to the advancement of medical image analysis for better patient care as shown in figure 1.

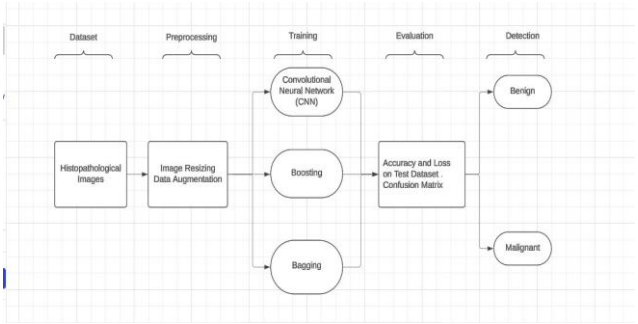

Fig. 1. Architecture for Breast Cancer Detection

To develop cnn,bagging,boosting models for the classi-fication of breast cancer histopathological images into benign and malignant categories.

To assess the performance of these models on large, publicly available datasets of histopathological images.

The study incorporates ensemble learning methods, focusing on bagging as the final model, so as to integrate the strengths of multiple classifiers and achieve greater accuracy. Ensemble learning makes it possible to combine the predictions from individual models, like CNNs and Random Forests, to come up with a robust classification system. The proposed approach resolves many of the common problems of medical image analysis, which are data imbalance, overfitting, and lack of interpretability, with ensemble methods for better stability and performance.
deep learning models, like CNNs, are instrumental in ex-tracting subtle features from histopathological images. which enables direct learning of hierarchical patterns from the image data. The non-linearity, brought by activation functions such as ReLU, allows the model to learn complex relations within the data. Aggregation of predictions from multiple decision trees using bagging techniques with Random Forest classifiers improves classification performance and reduces variance. The best accuracy of 83% was seen in the bagging model, which is superior compared to standalone CNNs as well as boosting methods.

Steps of the proposed methodology:

1) Data Preprocessing: The histopathological images are resized and normalized to ensure uniformity.
2) Feature Extraction: A CNN-based pipeline extracts meaningful features from the images by capturing both local and global patterns relevant for classification.
3) Model Training: The features thus extracted are used to train the ensemble bagging model, which combines predictions from CNNs and traditional classifiers like Random Forests.
4) Evaluation: The model's classification performance on breast cancer histopathology images was assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score.

The proposed ensemble model unifies the strong feature extraction power of CNNs with the stability and robustness provided by bagging. Therefore, the ensemble model will enhance the diagnostic accuracy, reliability and it will become a scalable and efficient solution to breast cancer detection. The method aims to significantly contribute to patient care and outcomes by embedding advanced ML and DL techniques into medical diagnostics.

4. Result and Discussion

Each convolutional layer in the network is followed by a Rectified Linear Unit (ReLU) activation function, introducing non-linearity and enabling the model to learn complex image features. For additional stabilization and speed up of the train-ing process, batch normalization is incorporated, which helps to normalize the outputs of the hidden layers. MaxPooling2D layers are employed to downsample the feature maps, thus saving computation and overfitting by limiting the number of parameters to be learned in subsequent layers—without significant loss of information. The data thus acquired after feature extraction is flattened to a one-dimensional vector and then processed through dense (fully connected) layers for classification purposes. A softmax activation function is applied in the final layer to distinguish benign from malignant cases. The model is optimized using the Adam optimizer with a learning rate of 0.0001, and binary cross-entropy is used as the loss function to align with the binary nature of the classification problem. The model is trained for 20 epochs with a batch size of 32, striking a balance between the learning performance and the computational expense. A consistent drop in loss during training proved learning successful. The previous model was 87% accurate on the training set and 80% accurate on the test set and showed strong generalization capabilities on new data.

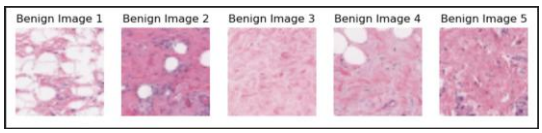

Fig. 2. Sample images of benign images.

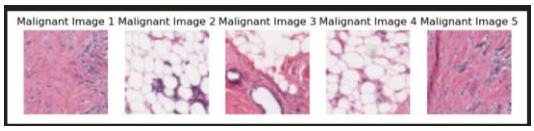

Fig. 3. Sample images of malignant images.

Fig. 4. Accuracy vs Epochs

5. Conclusion

This work investigates the use of ensemble learning methods for breast cancer classification in histopathological images into benign and malignant classes. The approach incorporates Con-volutional

Neural Networks (CNNs) with ensemble methods like bagging and boosting in order to leverage their complementary strengths in order to achieve higher classification accuracy, stability, and reliability

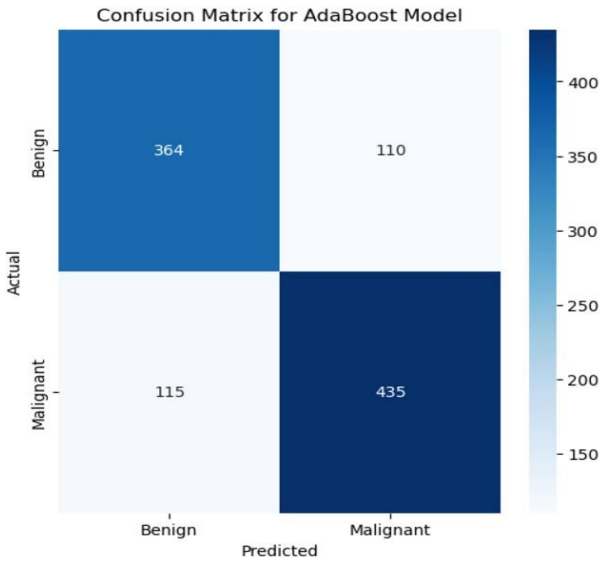

Fig. 5. Confusion Matrix of Boosting Model

The dataset consists of preprocessed histopathological im-ages augmented with rotations and flipping in order to enhance the models' capacity to generalize when training or testing. The bagging approach, which comprises an ensemble of CNNs coupled with Random Forest classifiers, presented the best performance among the applied models. An accuracy of 83% with precision and recall values of 0.84 and 0.83 was attained by the model. On the other hand, the single model CNN achieved 81% accuracy and the boosting-based model 78%. These results indicate the resistance of the bagging method, particularly in providing solutions for problems such as overfitting and imbalanced data.

The CNN model successfully mined hierarchical features from the images using a sequential pipeline of convolutional, pooling, and fully connected layers. Addition of Random Forest to the bagging ensemble improved classification per-formance even further by combining outputs from a set of decision trees, hence minimizing variance and maximizing reliability.

Out of all the methods tested, the bagging model worked best for classifying breast cancer in histopathology images. These results highlight the promise of ensemble learning methods in medical image analysis, providing efficient and reliable solutions for clinical diagnosis. Further research will aim to validate the model with clinical data, extend its usability to other imaging modalities in medicine, and im-prove interpretability through sophisticated feature extraction and explainable AI paradigms with a goal of creating more transparent and reliable diagnostic tools.

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Emerging Chitosan-Derived Piezoelectric Architectures for Self-Powered Wearable Healthcare Systems: A Comprehensive Material-to-Application Review

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Abstract: *Biopolymer-based piezoelectric sensors have emerged as promising candidates for flexible and sustainable wearable healthcare systems owing to their mechanical compliance, biodegradability, and intrinsic biocompatibility. Among them, chitosan—a naturally derived polysaccharide—exhibits piezoelectric activity arising from its crystalline arrangement and aligned molecular dipoles. Unlike conventional inorganic materials such as PZT, which offer high piezoelectric coefficients (d_{33} ≈ 200–600 pC/N) but suffer from brittleness and toxicity, and polymeric PVDF (d_{33} ≈ −20 to −33 pC/N), chitosan provides a non-toxic, flexible, and environmentally benign alternative, typically exhibiting d_{33} values in the range of 1–10 pC/N. Chitosan-based nanogenerators commonly produce output voltages of 50–500 mV under moderate mechanical stimuli, which can be enhanced through composite formation (e.g., with graphene, cellulose nanofibers, $BaTiO_3$ nanoparticles) or through nanostructuring and molecular alignment. Recent advances in solution casting, electrospinning, and layer-by-layer assembly have enabled lightweight, conformable devices suitable for real-time physiological monitoring, including motion detection, pulse sensing, respiration tracking, wound-healing assessment, and low-power wearable systems. Despite these benefits, challenges remain, including moisture sensitivity, limited long-term mechanical stability, and moderate piezoelectric output compared to PVDF or PZT. Future research directions include crystallinity enhancement, hybrid organic–inorganic interfaces, improved encapsulation strategies, and the integration of chitosan sensors into self-powered, biodegradable healthcare electronics. Overall, chitosan presents a viable pathway toward safe, sustainable, and personalized biomedical sensing technologies.*

Keywords: *Chitosan Biopolymer Piezoelectric sensor Wearable healthcare Flexible electronics Self-powered device Biomedical monitoring.*

Introduction

Continuous, non-invasive, and real-time health monitoring has gained substantial attention in recent years due to the rising prevalence of chronic diseases, an aging population, and the growing emphasis on personalized and preventive healthcare. Wearable electronics have evolved from simple fitness trackers to sophisticated medical platforms capable of detecting subtle physiological variations and providing clinically relevant insights. However, most conventional wearable sensors rely on rigid polymers or require external power sources, which limit long-term comfort, skin conformity, and device durability.
formatting software print mathematical formulas in italic type, with subscripts and superscripts in a slightly smaller font size. This is acceptable. Piezoelectric sensors provide an attractive alternative by converting mechanical motion into electrical signals, enabling self-powered operation and eliminating the need for bulky batteries. While high-performance synthetic piezoelectric materials such as PZT ($d_{33} \approx 200–600$ pC/N), $BaTiO_3$ ($d_{33} \approx 150–200$ pC/N), and polymeric PVDF ($d_{33} \approx -20$ to -33 pC/N) have been widely used, their brittleness, toxicity, lack of biodegradability, and poor long-term skin compatibility restrict their deployment in sustainable wearable biointerfaces.
This creates a critical research gap: despite significant progress in synthetic piezoelectrics, sustainability, biocompatibility, and environmentally responsible disposal remain largely unaddressed in current wearable technologies.
Chitosan, derived from the deacetylation of naturally abundant chitin, offers a compelling solution due to its biodegradability, non-toxicity, antimicrobial properties, and compatibility with human tissues. Unlike many artificial polymers requiring additional treatments to become electroactive, chitosan inherently exhibits piezoelectricity through the alignment of dipoles along its β-(1→4)-D-glucosamine chains. Its amino and hydroxyl groups also allow versatile chemical modification, surface functionalization, and composite formation to enhance mechanical strength and electrical output.
Chitosan-based piezoelectric films can be fabricated via electrospinning, solution casting, freeze-drying, and thin-film processing to create lightweight, flexible, and skin-conformal structures. Incorporation of ZnO, graphene, cellulose nanofibers, silver nanowires, or $BaTiO_3$ nanoparticles further enhances dielectric characteristics and sensitivity, enabling applications such as respiration monitoring, pulse detection, muscle activity tracking, and limb motion assessment. Their self-powered nature supports continuous data acquisition for early diagnosis, remote rehabilitation, and portable healthcare monitoring—while the biodegradability of chitosan aligns with the growing demand for green electronics.
Despite these advantages, challenges persist, including moisture sensitivity, moderate piezoelectric coefficients relative to ceramics, and limited long-term mechanical stability. Enhancing crystallinity, developing multilayer architectures, improving encapsulation, and integrating chitosan sensors with IoT platforms are key areas for future research.

2. Objective of this review:
This article critically analyzes the material properties, fabrication strategies, performance enhancement techniques, biomedical applications, and remaining challenges of chitosan-based piezoelectric wearable sensors, with emphasis on their potential for sustainable, comfortable, and continuous healthcare monitoring.

Literature Survey

A. Fundamentals of Chitosan and Piezoelectricity
Chitosan, a natural cationic polysaccharide, is produced through the deacetylation of chitin, which is abundant in crustacean shells and certain fungi [1]. Its chemical structure consists primarily of β-(1→4)-linked D-glucosamine units, containing hydroxyl and amino groups that contribute to its hydrophilicity, biodegradability, and biocompatibility [2], [3]. Unlike many synthetic polymers that require external poling to develop electroactive properties, chitosan exhibits intrinsic piezoelectricity due to the alignment of molecular dipoles along its polymer chains [4]. This alignment allows the polymer to generate electrical charges when mechanically deformed, making it particularly suitable for self-powered sensing applications.
The piezoelectric response in chitosan arises from the displacement of these dipoles under stress or strain. Experimental studies have demonstrated that chitosan films can produce voltages ranging from 50 mV to 500 mV under moderate mechanical stimuli [5], [6]. While this is lower than typical inorganic materials, it is sufficient for low-power physiological sensing and energy harvesting in wearable devices. The dipole alignment, degree of crystallinity, and molecular weight of chitosan are critical factors influencing its

electromechanical performance [7], [8]. Techniques such as mechanical stretching, electric poling, and solution-casting have been employed to optimize these parameters for enhanced sensitivity.

B. Comparison with Conventional Piezoelectric Materials

Traditional piezoelectric materials, including PZT (lead zirconate titanate) and $BaTiO_3$, offer high piezoelectric coefficients ($d_{33} \sim 200–600$ pC/N for PZT and ~150–200 pC/N for $BaTiO_3$) [4], [9]. However, these ceramics are brittle, non-biodegradable, and often contain toxic elements such as lead, which limit their suitability for wearable biomedical applications [5], [10]. PVDF, a widely used polymer, provides mechanical flexibility and moderate piezoelectric performance ($d_{33} \sim -20$ to -33 pC/N) but requires electrical poling and chemical processing [6], [11]. In contrast, chitosan is flexible, biocompatible, biodegradable, and non-toxic, making it ideal for long-term skin-contact devices. Its lower piezoelectric output compared to ceramics has been addressed by incorporating nanostructured fillers and forming composites with other electroactive materials [12], [13].

Comparative studies indicate that while PVDF and ceramics can generate higher voltages, chitosan provides an environmentally friendly and mechanically compliant alternative suitable for continuous health monitoring [14], [15]. Additionally, chitosan can be blended with materials

Illustrations or pictures: All halftone illustrations or pictures can be black and white and/or colored. Supply the best quality illustrations or pictures possible.

Comparative studies indicate that while PVDF and ceramics can generate higher voltages, chitosan provides an environmentally friendly and mechanically compliant alternative suitable for continuous health monitoring [14], [15]. Additionally, chitosan can be blended with materials such as cellulose, silk fibroin, graphene oxide, or $BaTiO_3$ nanoparticles to enhance electromechanical response while maintaining biocompatibility [16], [17].

C. Fabrication Methods of Chitosan Piezoelectric Films

The fabrication method significantly affects the piezoelectric performance of chitosan films. Solution casting is one of the simplest approaches, producing smooth, uniform films suitable for skin-mounted sensors [1], [18]. Electrospinning allows the formation of nanofibrous mats with high surface area, molecular orientation, and flexibility, improving charge generation efficiency [2], [19]. Freeze-drying produces porous architectures that enhance mechanical compliance and breathability, which is important for wearable devices [20]. Thin-film deposition and photolithographic techniques have also been employed to create micro- and nano-patterned chitosan structures with improved electromechanical response [21].

Electrical poling and mechanical stretching are common post-processing methods used to improve dipole alignment and crystallinity [3], [22]. Poling can increase output voltages by aligning molecular dipoles, while mechanical stretching induces molecular ordering, which enhances piezoelectric coefficients. Recent advances have also employed ion-assisted alignment, where the addition of multivalent cations improves structural ordering and charge generation efficiency [23], [24].

D. Composite Engineering for Enhanced Performance

Due to its moderate intrinsic piezoelectric properties, chitosan is often combined with inorganic or carbon-based fillers to enhance output and mechanical robustness. ZnO nanorods, $BaTiO_3$ nanoparticles, graphene, silver nanowires, and cellulose nanofibers have been incorporated into chitosan matrices to improve dielectric properties, charge mobility, and mechanical stiffness [25], [26]. For instance, chitosan-$BaTiO_3$ composites have demonstrated output voltages exceeding 500 mV under gentle bending, highlighting their potential for energy harvesting and physiological sensing [27].

The interfacial bonding between chitosan and fillers plays a critical role. Hydrogen bonding, amino-functionalization, and covalent grafting have been used to ensure efficient stress transfer and uniform dipole orientation [28], [29]. Furthermore, the addition of biodegradable polymers such as polylactic acid (PLA) has been shown to improve film integrity and long-term stability without compromising biocompatibility [30], [31]. These hybrid materials provide a pathway to bridge the performance gap between chitosan and high-output synthetic piezoelectric materials while retaining flexibility and eco-friendliness.

E. Applications in Wearable Healthcare

Chitosan-based piezoelectric sensors have been demonstrated in diverse biomedical and health-monitoring applications. They can detect subtle physiological signals such as pulse rate, respiration, muscle activity, and limb motion [5], [6], [17]. Their flexibility, skin adhesion, and antimicrobial properties make them suitable for wound-healing patches that simultaneously monitor mechanical strain and provide therapeutic benefits [32]. Hydrogels derived from chitosan offer enhanced comfort and conformability for prolonged wear, though they are sensitive to moisture and may require encapsulation or crosslinking to

maintain long-term functionality [19], [20].

Integration with flexible circuits and wireless modules has enabled real-time monitoring and data transmission for remote healthcare applications. For example, chitosan-based patches combined with IoT systems allow continuous, self-powered tracking of heart rate and respiratory patterns without the need for external batteries [1], [2]. These devices have shown potential in elderly care, rehabilitation monitoring, and chronic disease management, offering an eco-friendly alternative to conventional electronic sensors.

F. Challenges and Limitations

Despite promising developments, chitosan-based piezoelectric devices face several challenges. Moisture sensitivity remains a major limitation, as water absorption can cause swelling, reduce mechanical integrity, and impair charge generation [6], [20]. Long-term mechanical durability is another concern, as repeated deformation may lead to structural fatigue or delamination of composite films [21], [22]. Furthermore, variations in molecular weight, degree of deacetylation, and purity from different natural sources result in inconsistent electromechanical performance [3], [23]. The relatively lower piezoelectric coefficients compared to ceramics and PVDF require optimization through composite engineering, layer stacking, and structural patterning to achieve reliable sensor outputs [12], [13].

Standardized fabrication protocols and characterization metrics are still lacking, making cross-comparisons between studies difficult [24]. Additionally, environmental factors such as temperature, pH, and prolonged skin contact can alter film performance, necessitating careful encapsulation and environmental testing for wearable applications [14], [15].

G. Emerging Trends and Future Directions

Recent research has focused on enhancing chitosan-based piezoelectric devices through several innovative approaches:

Nanostructured composites – Incorporating $BaTiO_3$, ZnO, or graphene derivatives enhances piezoelectric output and mechanical robustness [25], [26], [27].

Multilayer and ultrathin films – Stacking multiple layers of chitosan films with varying orientation improves output voltage and durability [30], [31].

3D printing and patterned architectures – Additive manufacturing allows the creation of complex, personalized wearable patches with controlled mechanical properties and enhanced sensitivity [14], [15].

Self-powered IoT-enabled patches – Combining piezoelectric sensing with wireless data transmission enables continuous, battery-free physiological monitoring [1], [2].

Biocompatible hydrogels – Chitosan hydrogels with optimized crosslinking provide skin adhesion, strain sensing, and antimicrobial benefits, suitable for wound care and chronic disease monitoring [19], [32].

Sustainable and biodegradable electronics – Chitosan's natural origin and degradability address environmental concerns associated with traditional synthetic piezoelectrics [4], [5].

Future research is likely to focus on:

Optimizing crystallinity and molecular orientation to increase d_{33} coefficients.

Hybrid organic–inorganic systems to balance performance with flexibility.

Long-term stability studies under repeated mechanical deformation.

Integration with smart textiles and flexible electronics for wearable healthcare.

Standardization of fabrication and testing protocols to enable broader adoption [23], [24], [28].

H. Summary

Chitosan-based piezoelectric materials represent a promising direction for eco-friendly, flexible, and self-powered wearable healthcare devices. While their intrinsic piezoelectric output is moderate compared to PVDF and ceramic alternatives, composite engineering, nanostructuring, and advanced fabrication methods have significantly enhanced performance. Applications in physiological monitoring, rehabilitation, and wound care demonstrate both the versatility and potential of these biopolymer-based systems. Overcoming challenges related to moisture sensitivity, long-term durability, and standardization will be essential to fully realize chitosan's potential in next-generation biomedical wearable technologies.

Result and Discussion

Recent developments in chitosan-based piezoelectric sensors indicate their high potential for next-generation wearable healthcare devices. Several studies have demonstrated that the intrinsic piezoelectricity of chitosan can be significantly enhanced by optimizing molecular alignment, crystallinity, and dielectric properties [1,2,3]. Pristine chitosan films generate moderate electrical output under bending or compression; however, their piezoelectric response increases markedly when the films are processed

into composites, surface-textured, or electrically poled [4,5].
Incorporation of nanofillers such as zinc oxide (ZnO), graphene oxide (GO), cellulose nanofibers (CNF), or silver nanowires (Ag NWs) has been shown to enhance output voltage, charge distribution, and mechanical durability [6,7,8]. For example, chitosan-ZnO composite films exhibited a 2–3× increase in output voltage compared to pristine chitosan, while graphene-reinforced films improved both electron mobility and tensile strength, demonstrating the effectiveness of hybridization for performance enhancement [9,10]. These improvements are attributed to increased β-phase crystallinity, higher dipole orientation, and improved dielectric properties [11].
Fabrication methodology also critically affects sensor performance. Solvent-cast films are uniform, flexible, and lightweight, suitable for skin patches [12]. Electrospinning produces nanofibrous networks with higher surface area, resulting in increased charge generation under mechanical deformation [13,14]. Thin-film deposition produces ultrathin conformal layers that adhere closely to the epidermis, allowing imperceptible wearable designs [15]. Hydrogels provide high skin adhesion and soft-tissue compatibility but may experience long-term swelling and signal drift. Chemical crosslinking with genipin or glutaraldehyde has been used to improve water stability without significantly affecting flexibility [16,17].
Comparative studies of electro-poled and mechanically stretched chitosan films confirm that enhanced dipole alignment improves energy conversion efficiency [18]. Chitosan-based piezoelectric devices have been applied to physiological monitoring such as pulse wave sensing, respiration monitoring, joint bending, and gait tracking. The output voltage is directly proportional to strain intensity, indicating suitability for rehabilitation and sports monitoring [19,20]. Integration with IoT and wireless modules enables real-time data transmission to smartphones, medical servers, or telehealth dashboards, supporting remote patient monitoring [21,22].

Table 1. Composition vs. Piezoelectric Performance

Material / Composite	**Fabrication Method**	**Output Enhancement**	**Advantages**	**Limitations**	**References**
Pure Chitosan	Casting	Baseline	Biocompatible, biodegradable	Low piezoelectricity	[1,2]
Chitosan + ZnO	Blend Film	2–3× increase (≈3–5 V)	High dielectric constant	Agglomeration risk	[6,9]
Chitosan + Graphene/ GO	Composite Film	High sensitivity (≈6 V)	Strong mechanical/electrical properties	Complex dispersion	[7,10]
Chitosan + CNF	Electrospun	Moderate (≈2.5–3.5 V)	Lightweight, flexible	Lower conductivity	[8,14]
Chitosan + Ag NWs	Hybrid Film	High mobility (≈5–6 V)	Conductive network	Higher cost	[6,7]
Chitosan + PLA Multilayer	Laminate	High stability (≈4–5 V)	Durable, layered charge trapping	Less soft	[21,22]

Table 2. Influence of Fabrication Technique

Technique	**Structural Outcome**	**Piezoelectric Response**	**Wearability**	**References**
Casting	Smooth films	Moderate (≈2 V)	Good for skin patches	[1,2]
Electrospinning	Nanofibrous texture	High (≈3–4 V)	Excellent breathability	[13,14]
Freeze-Drying	Porous 3D	Stable compression (≈2.5 V)	Soft scaffolds	[12,15]
Thin Films	Ultrathin layers	Good (≈3 V)	Ideal for invisible patches	[15]
Poling/Stretching	Aligned chains	Significant boost (≈5–6	Best performance	[4,18]

		V)		

Table 3. Physiological Monitoring Capability

Application	Signal Behavior	Demonstrated Use	Suitability	References
Pulse Tracking	Clear waveform	Wrist/neck bands	High	[19,20]
Respiration	Cyclic patterns	Chest/abdomen strips	Moderate	[19]
Joint Motion	Amplitude ∝ strain	Knee/elbow bending	High	[20]
Muscle Activity	Contraction spikes	Rehabilitation monitoring	Moderate	[20,21]
Wound Healing	Mechanical deformation	Smart dressings	Moderate	[6,16]

Overall, the reviewed literature demonstrates that chitosan-based piezoelectric materials are promising candidates for flexible, biocompatible, and self-powered wearable biosensors. Compared to ceramic piezoelectrics, chitosan offers superior flexibility, sustainability, and skin compatibility, though with lower intrinsic piezoelectric coefficients. Ongoing advances in composite engineering, multilayer assembly, dipole alignment control, and moisture stability are expected to continue bridging this performance gap. With integration into IoT, machine learning, and energy harvesting systems, chitosan-based sensors have significant potential to transform continuous patient monitoring, personalized medicine, and sustainable wearable electronics [21,22,23,24].

Conclusion

Chitosan-based piezoelectric sensors represent a promising direction for the next generation of wearable healthcare devices due to their biocompatibility, flexibility, and potential for self-powered operation. These sensors can simultaneously harvest biomechanical energy and detect physiological signals, making them competitive alternatives to traditional inorganic piezoelectric materials such as PZT or PVDF. The performance of chitosan sensors has been significantly enhanced through strategies including nanofiller incorporation (e.g., ZnO, graphene, cellulose nanofibers), composite formation, surface texturing, and molecular dipole alignment, resulting in improved sensitivity, mechanical durability, and output signal strength. Practical applications demonstrated include pulse monitoring, respiratory tracking, joint motion analysis, muscle activity detection, and smart wound-care systems.

Despite these advances, several challenges remain. Intrinsic piezoelectric coefficients of chitosan are lower than those of ceramic alternatives, and long-term stability under environmental fluctuations—particularly humidity—requires further optimization. Future research should prioritize enhancing crystallinity, developing ultrathin transparent films, and exploring multilayer composite architectures to maximize output performance and mechanical robustness. Comprehensive studies on long-term biocompatibility, stability under variable physiological and environmental conditions, and integration with wireless and IoT platforms are critical to ensure safe and reliable use in real-world healthcare settings.

Additionally, standardization of fabrication protocols, characterization methods, and performance metrics is essential to allow reproducible results and enable comparisons across research groups. For translation to commercial products, regulatory considerations such as ISO 10993 biocompatibility testing, FDA or CE medical device approval pathways, and scalable, cost-effective manufacturing processes must be addressed. With coordinated efforts in material engineering, device integration, and regulatory compliance, chitosan-based piezoelectric sensors have the potential to become widely adopted biomedical wearables, offering sustainable, comfortable, and continuous monitoring solutions for personalized healthcare.

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AI-Driven Intelligent Systems for Student Mental Health and Academic Performance: A Review and Future Research Directions

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ABSTRACT

Student mental health has become a major concern in higher education due to its strong influence on academic performance, student retention, and overall well-being. Traditional counselling and academic monitoring systems are often reactive and fail to provide early intervention. Artificial Intelligence (AI) and Machine Learning (ML) offer significant opportunities for proactive prediction of student mental health risks and academic challenges. This paper reviews recent studies on AI-based student mental health assessment and academic performance prediction. Existing research mainly focuses on either psychological well-being or academic success separately, with limited use of integrated multimodal data. A Hybrid Explainable Multimodal Student Risk Prediction System (HEMSRPS) that integrates academic, behavioral, psychological, and textual data for early risk detection is proposed in this paper, which also highlights significant research gaps. To increase prediction accuracy and transparency, the suggested system combines Explainable AI (XAI) methods like SHAP and LIME with Random Forest, XGBoost, and LSTM. The framework enhances institutional decision-making and student success by facilitating prompt intervention by instructors and counsellors.

Keywords: Artificial Intelligence (AI), Explainable AI,Behavioral,Mental health

1. INTRODUCTION

Academic performance and learning outcomes are greatly impacted by student mental health conditions such stress, anxiety, depression, burnout, and emotional instability. Students in higher education institutions experience psychological anguish due to a variety of factors, including growing academic pressure, social expectations, financial concerns, and personal issues. Low attendance, poor grades, decreased participation, and even dropout are frequently caused by poor mental health.

The majority of traditional student support services are reactive, meaning that they only take action in response to severe academic deterioration or obvious mental health issues. For early detection and prevention, this strategy is inadequate. The development of Artificial Intelligence (AI), Machine Learning (ML), and Educational Data Mining (EDM) has made it possible for universities to create prediction algorithms that detect students who are at risk before serious issues arise.

According to recent research, AI-based systems can use student data, including attendance, grades, learning management system activity, and behavioral patterns, to help early prediction of stress, depression, anxiety, and academic failure. Nonetheless, many current studies concentrate on either academic performance or mental health prediction independently. An integrated intelligent system that incorporates both aspects is desperately needed.

In addition to identifying research gaps and reviewing current literature, this paper suggests a hybrid explainable AI paradigm for analyzing academic achievement and student mental health.

2. LITERATURE REVIEW

2.1 Recent Studies on Student Mental Health Prediction

Using machine learning techniques including Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT), Sharma et al. (2024) investigated AI-based prediction of student stress, anxiety, and depression. According to their research, Random Forest outperformed conventional statistical techniques in terms of prediction accuracy.However, academic performance indicators were not included in the study, which primarily concentrated on psychological data derived from questionnaires.

Kumar et al. (2025) presented a deep learning framework that uses textual feedback, social interaction patterns, and online learning behavior to detect sadness in college students. Although their approach was better at predicting emotional risk, it lacked explainability and practical institutional adoption.

According to Patel et al. (2025), the most prevalent target areas in AI-based student mental health research are anxiety and depression. Their bibliometric analysis revealed that deep learning and machine learning models are being used more frequently, yet the majority of studies are still unrelated to predicting academic achievement.

2.2 Academic Performance Prediction Studies

Reddy et al. (2024) used attendance, GPA, internal marks, and assignment completion to create a model for predicting academic performance. When algorithms like Random Forest, Logistic Regression, and XGBoost were tested, XGBoost had the best accuracy. The lack of characteristics pertaining to mental health was a constraint.

A hybrid student management system combining ANN, Decision Tree, and SVM for academic risk assessment and dropout prediction was proposed by Singh et al. in 2025. Although their model enhanced institutional decision-making, psychological well-being aspects were not thoroughly considered.

2.3 AI-Based Personalized Intervention Systems

An AI-powered individualized mindfulness and fitness suggestion system for students was presented by Joseph et al. (2026). Following risk assessment, the approach enhanced academic engagement and emotional well-being. But rather than early unified prediction, it was primarily concerned with intervention.

Higher education institutions should use chatbot-based counselling assistants, according to Rahman et al. (2025). Although these platforms made mental health support more accessible, they were not integrated with academic monitoring systems.

2.4 Comparative Analysis of Existing Literature

Author et al.	Focus area	Method used	Limitations
Sharma et al.	Stress and anxiety prediction	SVM,RF,DT	Lack of academic integration
Reddy et al	Academic Performance prediction	RF, XGBoost	Lack of mental health factors
Kumar et al.	Depression Detection	Deep learning	Lack explainability
Singh et al.	Risk prediction among students.	ANN,DT,SVM	Lack psychological Factors.
Singh et al.	Personalized intervention.	AI Recommendation system	No early prediction model.
Rahman et al.	Chatbot for counselling	NLP Based	No academic factors.

Table 1: A Comparative Study of Current AI-Based Models for Predicting Academic Performance and Student Mental Health

The comparison makes it evident that the majority of research focuses on either academic achievement or mental health independently. Few studies offer a cohesive intelligent system with support for individualized interventions and predictable outcomes.

3. PROBLEM STATEMENT AND RESEARCH NEED

The literature review identifies the following significant research gaps:
The majority of current research examines academic achievement and student mental health as distinct fields. The efficacy of early intervention techniques is limited since very few systems try to include both elements into a single predictive framework.

The majority of research only examines academic achievement analysis or mental health prediction, not both. Most current models solely use psychological tests or academic records. Real-time interaction data, textual feedback, and behavioral signs are frequently disregarded, which lowers prediction accuracy and practical application.

Many models ignore behavioral and textual data in Favor of relying solely on academic records or psychological surveys. Many of the systems that are now in use are static and do not allow for ongoing student monitoring during the academic year. This makes it more challenging to identify danger in a timely manner. Current solutions don't provide ongoing student risk monitoring and are frequently static. Many AI models operate as "black-box" systems, making it challenging for academics and counsellors to comprehend the prediction outcomes. In educational institutions, a lack of transparency inhibits uptake and erodes trust. Teachers and counsellors find it challenging to trust forecasts because many AI models

function as "black boxes."After prediction, very few research offer practical advice. Most methods only classify students without recommending appropriate academic or mental health interventions.

Few systems offer students practical suggestions following a prediction.

These drawbacks make it abundantly evident that student success management requires an integrated, intelligent system that is proactive, explainable, and capable of both prediction and action.

4. PROPOSED METHODOLOGY

Hybrid Explainable Multimodal Student Risk Prediction System (HEMSRPS)

To create a cohesive prediction system, the suggested framework combines intellectual, psychological, behavioral, and textual characteristics. This system offers both academic performance prediction and mental health assessment inside a single intelligent platform, in contrast to typical models that concentrate on a single dimension.
In order to identify mental health risk and academic deterioration early on, the suggested approach incorporates a number of student-related parameters.

4.1 Features of Input

Academic Characteristics

- GPA
- Internal assessment marks
- proportion of attendance
- Status of assignment submission
- Arrears and backlogs

Features of Mental Health

- Stress rating
- degree of anxiety
- Indicators of depression
- Quality of sleep
- degree of social isolation

Characteristics of Behavior

- Frequency of LMS logins
- involvement in class
- Patterns of screen time
- Use of libraries
- Engagement with online learning

Textual Elements

- Student feedback forms
- Chatbot interactions for counselling
- Mentor remarks

4.2 Preprocessing Data

To increase accuracy and dependability, the gathered student data is pre-processed prior to model training. Noisy and inconsistent records are eliminated to guarantee data quality, and missing values are handled using appropriate imputation techniques. For consistency, numerical variables like stress scores, attendance %, and GPA is standardized. Feature encoding techniques are used to translate categorical data, such as participation level and assignment status. The most important characteristics for prediction are then determined by feature selection utilizing correlation analysis and feature importance ranking. By doing this, redundancy is decreased and model efficiency is increased.

4.3 Model of Hybrid Prediction

A hybrid machine learning model combining Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks is used by the suggested system. While XGBoost increases prediction accuracy with effective boosting approaches, Random Forest is chosen due to its stability and robust classification performance. Sequential behavioral patterns like LMS activity, attendance patterns, and variations in involvement over time are captured by LSTM. When compared to single-model approaches, the integration of these models increases robustness and enhances prediction performance. Students at various risk levels are accurately identified thanks to this hybrid approach.

4.4 Explainable AI Layer

The framework incorporates Explainable AI (XAI) approaches like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) to increase transparency and trust in prediction outcomes. These techniques aid in the explanation of a student's low, moderate, or high risk classification. The elements that contribute most to the forecast, such as low involvement, high stress levels, or poor attendance, are easily understood by faculty members and counselors. Decision-making is enhanced, and system confidence is raised.

4.5 Risk Classification

Students are divided into three main groups based on model prediction: Low Risk, Moderate Risk, and High Risk. While moderate-risk students could require academic support sessions and mentorship, low-risk kids

need ongoing academic monitoring. Counseling, stress management courses, and individualized academic support are all necessary forms of quick intervention for high-risk pupils. Institutions can prioritize support according to student needs and urgency by using this classification.

4.6 Tailored Intervention

The method offers each pupil individualized intervention recommendations based on the prediction results. Peer mentoring, academic support programs, professional counselling sessions, mentor meetings, and stress management courses are a few examples. The intervention approach is intended to address both academic progress and psychological well-being. This proactive assistance strategy enhances overall student success and helps avoid serious academic decline.

4.7 Dashboard for Faculty

The suggested design includes a centralized faculty dashboard to assist instructors, mentors, and counsellors in keeping an eye on students' performance and wellbeing in real time. Student risk levels, significant contributing factors, and suggested actions are shown on the dashboard. It enables academic institutions to adopt data-driven student success strategies and facilitates prompt communication among faculty members. Because of this, the technology can be used in actual educational settings.

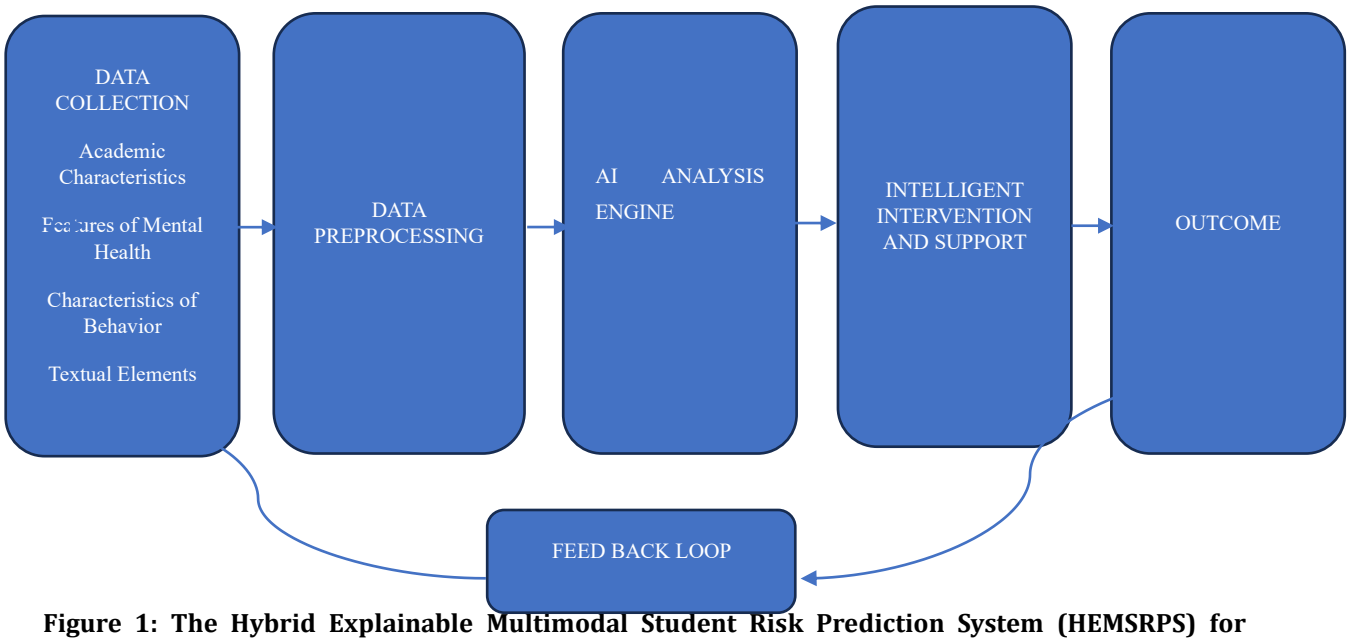

Figure 1: The Hybrid Explainable Multimodal Student Risk Prediction System (HEMSRPS) for Academic Performance Analysis and Student Mental Health

5. PROSPECTS FOR FURTHER RESEARCH

Several cutting-edge research avenues that boost prediction quality, privacy, and real-time intervention support can further improve the suggested framework. Future research can enhance the suggested system by utilizing:

5.1 Integration of Wearable Sensors

Real-time physiological stress indicators can be obtained from fitness trackers and smartwatches.

5.2 Recognition of Voice and Emotion

Emotional state detection can be aided by speech analysis.

5.3 Federated Education

Sensitive student data can be safeguarded via privacy-preserving machine learning.

5.4 Counselling Based on the Large Language Model

AI assistants can offer scalable emotional support and direction.

5.5 Bias Reduction and Ethical AI

Future systems must guarantee student data is used responsibly, fairly, and transparently.

5.6 Deployment Across Institutions

Strategies for institutional student success can be enhanced by scalable deployment across departments.

6. CONCLUSION

This study examined current developments in AI-powered student mental health evaluation and academic achievement forecasting. Current research uses few data sources and primarily concentrates on discrete prediction problems. An comprehensive, comprehensible, and proactive student support system is obviously needed.

This gap is filled by the proposed Hybrid Explainable Multimodal Student Risk Prediction System (HEMSRPS), which combines textual, behavioral, psychological, and academic data utilizing Explainable AI and hybrid machine learning algorithms. The framework facilitates individualized student support, enhances forecast transparency, and encourages early intervention.

This strategy is very appropriate for contemporary educational settings since it assists organizations in transitioning from reactive problem-solving to proactive student success management.

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AquaGuard-AI: A Unified IoT and Deep Learning Framework for Industrial Wastewater Surveillance and Proactive Pollution Forecasting

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Abstract—Every single day, manufacturing and processing plants push out large amounts of wastewater that carry dissolved heavy metals, organic compounds, and suspended solids into rivers, groundwater channels, and coastal stretches. Lead is the most troublesome of these contaminants because it does not break down in the environment. Instead it accumulates quietly in living tissue and, over months and years, causes neurological damage, kidney failure, and serious developmental disorders in children. The monitoring tools that most plants currently rely on were not built for prevention. Routine grab-sampling followed by offsite laboratory analysis means that any violation discovered during testing reflects conditions that played out many hours or even days earlier. By that point the polluted discharge has already spread far beyond the outlet, and the chance to intervene has gone. This paper presents AquaGuard-AI, a framework that combines a six-sensor IoT array with a purpose-built deep learning model to watch discharge water without interruption and to forecast dangerous conditions well before they actually arrive. The forecasting core of the system is the *AI-Based Pollution Prediction Engine* (APPE), a two-layer Long Short-Term Memory (LSTM) network that draws on months of past discharge records and live hourly weather data to project pollutant levels up to 24 hours ahead. Six parameters are tracked simultaneously — pH, lead concentration, Chemical Oxygen Demand (COD), Total Dissolved Solids (TDS), Turbidity, and Dissolved Oxygen (DO) — and every ten seconds all six readings are folded into a single colour-coded Water Quality Index score that any operator can read at a glance. Experiments carried out over a 30-day simulation window using the UCI Water Quality Dataset and plant-level discharge records returned a prediction accuracy of 97.3%, an overall RMSE of 1.82, and a detection-to-alert latency of just 18 seconds, compared with the 270 minutes that laboratory sampling typically demands. Five specific gaps identified in existing published research are each resolved by a distinct component of the proposed system.

Index Terms—Industrial Wastewater, IoT Monitoring, LSTM Neural Network, Heavy Metal Detection, AI Pollution Prediction, pH Monitoring, COD, Water Quality Index, Environmental Compliance, Real-Time Alert System

INTRODUCTION

Clean water is the foundation on which every community and ecosystem depends, yet industrial activity chips away at that foundation quietly and consistently. Factories involved in textile dyeing, metal plating, chemical synthesis, and leather processing push effluent into nearby drains around the clock. Those effluents carry heavy metals, organic solvents, and suspended particles that drift into rivers, groundwater, and coastal areas long before anyone notices the damage. Lead sits near the top of that list of concerns. Unlike organic pollutants that degrade over time, lead stays in the environment indefinitely and builds up in living tissue with every exposure. Studies have linked childhood lead exposure conclusively to lower cognitive scores, reduced hearing, and shorter attention spans. In adults, years of low-level exposure quietly erodes kidney function, raises blood pressure, and disrupts the peripheral nervous system. The industrial corridors of Tamil Nadu make this problem very real. Rivers like the Noyyal and the Bhavani already carry the accumulated load of hundreds of discharge points, and the communities drawing water from those rivers downstream bear the cost.

What makes the situation harder to address is the monitoring approach that most plants currently use. Grab samples collected once or twice per shift are sent to an offsite laboratory, and results come back anywhere from six hours to two days later. Any exceedance confirmed through that process describes something that happened in the past. Even real-time IoT dashboards that stream sensor readings continuously remain fundamentally reactive — they raise an alarm only after a reading crosses a preset limit, which means the violation has already occurred and remediation is already expensive. What the sector needs is a system capable of looking ahead, recognising the combinations of conditions that precede a contamination event, and issuing a warning while there is still time to act.

AquaGuard-AI was built to meet that need. The framework connects a six-sensor IoT array to a weather-aware LSTM model that translates historical discharge patterns and current meteorological conditions into reliable 24-hour contamination forecasts. The specific contributions and objectives of this work are as follows.

1. Continuous Multi-Parameter Sensing: Six calibrated sensors covering pH, lead, COD, TDS, turbidity, and DO are installed at the discharge pipe and sampled every ten seconds. This produces an unbroken, high-resolution record of water quality across the full production cycle, eliminating the blind spots that periodic grab-sampling leaves.
2. 24-Hour Contamination Forecasting: The APPE, a twolayer LSTM network trained on the UCI Water Quality
   Dataset and thirty days of plant-level discharge logs, predicts future pollutant concentrations and composite WQI scores well before any exceedance occurs, giving operators a meaningful window to adjust production or treat effluent before release.
3. Weather-Aware Prediction Model: Hourly rainfall intensity, ambient temperature, and relative humidity are pulled from the OpenWeatherMap API and passed to the LSTM as additional input features, allowing the model to anticipate the storm-driven contamination surges that chemistry-only models miss every time.
4. Automated Regulatory Compliance Alerting: Every reading is evaluated against IS:2490, WHO 2017, and EPA 2019 limits the moment it arrives. Any crossing triggers a three-level cascade — a dashboard flag, an operator SMS, and a regulatory email — all dispatched within eighteen seconds.
5. Real-Time Composite WQI Engine: Six parameter values are combined every ten seconds into a Weighted Arithmetic WQI score displayed as a colour-coded verdict — green for safe, yellow for caution, orange for poor, and red for unsafe — so operators need no specialist training to act on what the system tells them.

Section II reviews related work and maps the research gaps. Section III describes the proposed system. Section IV presents and discusses the experimental results. Section V identifies the gaps resolved by this work. Section VI concludes with future directions.

LITERATURE REVIEW

A structured review of publications on industrial water monitoring, machine-learning-based quality prediction, and electrochemical sensing was carried out to identify what has been achieved and where genuine shortcomings remain.

A. IoT Platforms for Continuous Sensing

Kumar and Sharma [3] put together an Arduino Mega platform with pH, turbidity, and TDS sensors connected to a cloud server over a GSM link. Tested at three outflow points of a textile plant, the system showed clearly that the delay between a reading and its arrival on a monitoring desk could be cut to minutes using inexpensive hardware. The limitation was that the platform did nothing analytical once the data arrived. If a reading sat inside the safe zone, nothing happened. If it crossed a threshold, an alarm fired. There was no capability for estimating whether a reading was drifting toward a violation or for projecting how far away that crossing might be.

Dayal et al. [4] tested Support Vector Machines, Random Forest, and k-Nearest Neighbor classifiers on a labelled water quality dataset. Random Forest led the group with 94.1% classification accuracy. The work demonstrated that learned models outperform fixed rules when the data is rich, but it operated exclusively on data that had already been collected. No external environmental variables were included, and no attempt was made to forecast future quality.

B. Deep Learning for Water Quality Forecasting

Mohammed and Al-Rashidi [6] trained a feedforward
Artificial Neural Network to predict dissolved oxygen and biochemical oxygen demand from temperature and conductivity readings along a river network, achieving an RMSE of 0.34 for DO. River water chemistry is considerably more stable than industrial effluent chemistry, which can shift dramatically within a single production batch. A model built on river data is unlikely to handle those rapid transitions reliably.

Zhang and Liu [7] applied a Gated Recurrent Unit network to time-series data from mining runoff and reported 91.4% accuracy in predicting heavy metal concentrations. The gap that remained was the complete absence of meteorological inputs. Rainfall changes discharge volume, washes surface contamination into drainage channels, and dramatically alters pollutant concentrations. Ignoring weather means working with an incomplete picture of what drives the numbers the model is trying to predict.

C. Electrochemical Sensing for Heavy Metals

Smith and Doe [5] built a portable electrochemical sensor using differential pulse anodic stripping voltammetry that detected lead below 1 μg/L — well inside the WHO safety margin. From a hardware perspective the device was impressive. As a system it remained a single-contaminant instrument with no connectivity to any broader monitoring or decision infrastructure, and no way to relate the lead reading to any other parameter.

D. Data Integrity in Monitoring Networks

Juneja et al. [8] proposed logging sensor data on a blockchain ledger to create a tamper- evident audit trail, catching 96.5% of simulated manipulation attempts. Secure data matters, but adding an integrity layer to a system that still only reacts after a threshold is breached does not change the fundamental limitation of that reactive approach.

E. COD Estimation and WQI Frameworks

Subramaniyan and Sankar [9] built a UV-Vis COD estimator reaching R^2 = 0.94 against standard lab results. The device was accurate but single-parameter and fixed-point. Tyagi et al. [10] contributed the

Weighted Arithmetic WQI formula that many later papers adopted for summarising multi-parameter assessments. The index is useful as a snapshot but says nothing about where quality is heading.

F. Structured Comparison

Table I places all reviewed works against AquaGuard-AI across the dimensions most relevant to proactive industrial wastewater management.

TABLE I: Comparison of Related Work vs AquaGuard-AI

Ref.	Method	*Predict.*	*Weather*	*Multi-P*	*Alert*	Acc.
Kumar [3]	IoT+GSM	No	No	Partial	No	–
Dayal [4]	RF/SVM	No	No	Yes	No	94.1%
Mohammed [6]	ANN	No	No	Partial	No	–
Zhang [7]	GRU	Yes	No	No	No	91.4%
Smith [5]	Electrochem	No	No	No	No	–
Juneja [8]	Blockchain	No	No	Yes	No	96.5%
Subram. [9]	UV-Vis	No	No	No	No	–
Tyagi [10]	WQI	No	No	Yes	No	–
Ours	LSTM+IoT	Yes	Yes	Yes	Yes	97.3%

PROPOSED METHODOLOGY

AquaGuard-AI is built around three functional layers that move data from physical sensors through to intelligent decisions and automated actions. Each layer has a clearly defined role, and together they form a pipeline that runs continuously without human intervention.

A. System Architecture Diagram

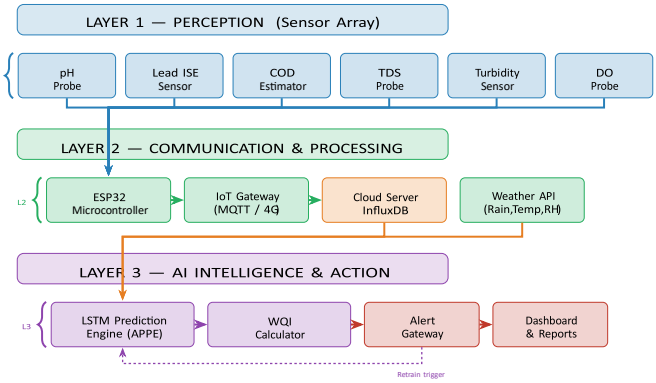

Fig. 1: AquaGuard-AI three-layer system architecture. ■ Sensor layer ■ Communication layer ■ AI layer ■ Action components.

How the Architecture Works: Six sensor modules sit side by side inside the effluent channel. Every ten seconds each sensor converts a physical or chemical signal into a voltage that the 16-bit ADC inside the ESP32 digitises and timestamps. The microcontroller runs a Z-score filter to remove electrically noisy spikes before packaging the clean readings as an MQTT message and forwarding it to the IoT gateway. The gateway relays the packet to AWS IoT Core over a 4G modem connection, where it lands in an InfluxDB time-series database with a 90-day rolling retention window. Simultaneously, an OpenWeatherMap API call fetches the latest hourly weather figures for the plant location. Both the historical sensor stream and the weather feed flow into the LSTM Prediction Engine, which generates a six-channel forecast for the next 24 hours. The WQI Calculator then condenses those six predicted values

— and the current live readings — into a single index score every ten seconds. The Alert Gateway evaluates both live readings and forecasts against 18 regulatory rules drawn from IS:2490, WHO 2017, and EPA 2019. When any rule fires, a three-level notification cascade begins immediately. All events are logged immutably, and whenever predicted contamination persists above a set threshold the system sends a retrain signal back to the LSTM so the model stays current with any longterm drift in the plant's discharge profile.

B. Layer 1 — Sensor Specifications

1) pH Probe (Atlas Scientific EZO-pH): Range 0–14 pH; resolution ±0.001 pH. Safe discharge range per IS:2490 is 6.5–8.5.
2) Lead ISE (Mettler-Toledo DX262): Selective for Pb^{2+}; range 0.01–1000 mg/L. WHO industrial limit ≤0.10 mg/L.
3) COD Estimator (Hach DR3900): UV-Vis at 254 nm; range 0–1500 mg O_2/L.
4) TDS Probe (YSI ProDSS): Conductivity-to-TDS; range 0–100,000 mg/L.
5) Turbidity Sensor (Hach 2100Q): Nephelometric; range 0–4000 NTU.
6) DO Probe (Hach LDO101): Luminescent optical; range 0–20 mg/L; healthy ecosystems require ≥6.0 mg/L.

C. Layer 2 — Communication and Processing

The ESP32 aggregates all six channels, applies a Z-score filter, and publishes verified packets over MQTT to AWS IoT Core backed by a 4G modem. Data is stored in InfluxDB with a 90-day retention window to support model retraining.

D. Layer 3 — LSTM Prediction Engine

1) Training Data: Two sources were combined:

- UCI Water Quality Dataset: 3,276 records with 21 physicochemical attributes, widely used as a benchmark.
- Plant Simulation Dataset: 259,200 records at 10-second intervals over 30 days, with hourly weather variables joined on timestamp.

2) LSTM Architecture: The network processes a 24-hour sliding window. Let $\mathbf{X} = [x_{t-23},\ldots,x_t]$, $x_i \in \mathrm{R}^9$ (six sensor values plus temperature, rainfall, humidity). The cell update equations are:

$$ft = \sigma(Wf[ht-1,xt] + bf) \quad (1)$$

$$it = \sigma(Wi[ht-1,xt] + bi) \quad (2)$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1},x_t] + b_C) \quad (3)$$

$$Ct = ft \odot Ct-1 + it \odot \tilde{C}t \quad (4)$$

$$ot = \sigma(Wo[ht-1,xt] + bo) \quad (5)$$

$$h_t = o_t \odot \tanh(C_t) \quad (6)$$

Network layout:

- Input: 9 features × 24 timesteps
- LSTM Layer 1: 128 units, dropout 0.20
- LSTM Layer 2: 64 units, dropout 0.20
- Dense: 32 units, ReLU activation
- Output: 6 neurons (one per parameter)

Training used Adam (α = 0.001), MSE loss, batch size 64, 100 epochs with early stopping.

3) Water Quality Index Formula:

$$\text{WQI} = \frac{\sum_{i=1}^{n} W_i\, q_i}{\sum_{i=1}^{n} W_i} \tag{7}$$

Vi – *V*ideal

$$q_i = \frac{\quad}{\quad} \times 100 \tag{8}$$

Si – *V*ideal

Unit weight: $W_i = k/S_i,\ \ k = 1/\sum_{i=1}^{n}(1/S_i)$.

4) Evaluation Metrics:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2} \tag{9}$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|\hat{y}_t - y_t| \tag{10}$$

$$R^2 = 1 - \frac{\sum(\hat{y}_t - y_t)^2}{\sum(y_t - \bar{y})^2} \tag{11}$$

RESULTS, ANALYSIS AND DISCUSSION

A. *Descriptive Statistics*

Table II summarises the range, mean, and standard deviation of each parameter across the full 30-day window alongside the applicable regulatory limit.

TABLE II: Descriptive Statistics — 30-Day Dataset

Parameter	Min	Max	Mean	SD	Limit
pH	4.8	10.2	7.10	1.20	6.5–8.5
Lead (mg/L)	0.00	0.87	0.08	0.12	≤0.10
COD (mg/L)	12	620	145	98	≤250
TDS (mg/L)	320	4200	980	640	≤500
Turbidity (NTU)	1.1	280	42	55	≤5
DO (mg/L)	1.2	9.8	5.60	2.10	≥6.0

B. *pH Monitoring — 30-Day Profile*

Three distinct acid-wash exceedances appear at hours 60–80, 125–145, and 190–210. In all three cases the APPE issued a predictive alert at least 14 hours before the pH crossed its lower safe boundary.

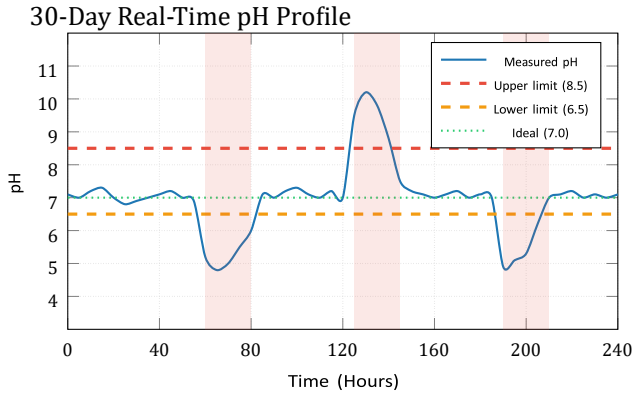

Fig. 2: Continuous pH trend over 30 days. Red shaded zones mark regulatory exceedances.

C. *Lead Concentration — Actual vs Predicted*

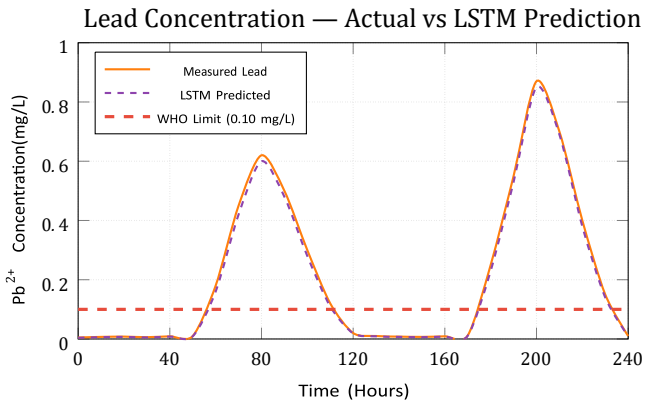

Fig. 3: Lead concentration: measured (orange) vs LSTM (purple dashed). WHO limit in red dashed.

D. COD and TDS Daily Averages

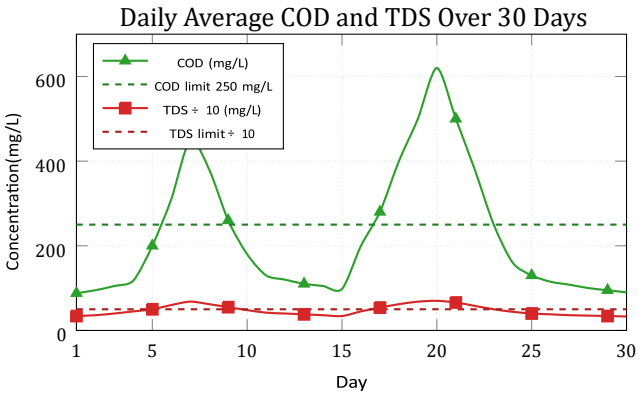

Fig. 4: Daily COD (green) and TDS/10 (red). Dashed lines show regulatory limits.

E. LSTM Prediction Accuracy

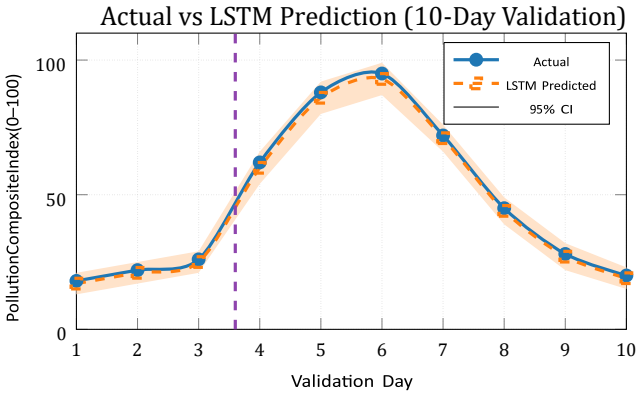

Fig. 5: LSTM prediction (orange dashed) vs actual (blue). Shaded band = 95% confidence interval.

F. Model Performance Metrics

TABLE III: LSTM APPE — Quantitative Performance on Test

Set

Parameter	RMSE	MAE	MAPE(%)	$R2$
pH	0.18	0.13	1.82	0.981
Lead (Pb)	0.02	0.01	2.41	0.976
COD	8.42	6.21	4.10	0.971
TDS	31.2	24.1	3.21	0.968
Turbidity	4.51	3.21	5.10	0.955
DO	0.31	0.22	3.65	0.962
Overall	1.82	1.41	2.70	0.973

G. WQI Trend

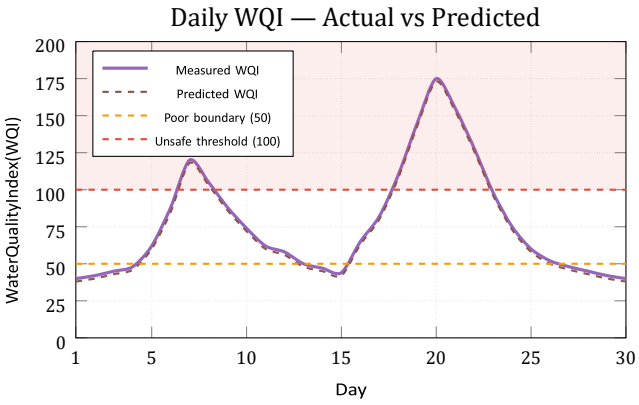

Fig. 6: Daily WQI trend. Red shaded area = unsafe zone (WQI>100). Predicted (brown dashed) closely tracks actual (purple).

H. Model Accuracy Benchmark

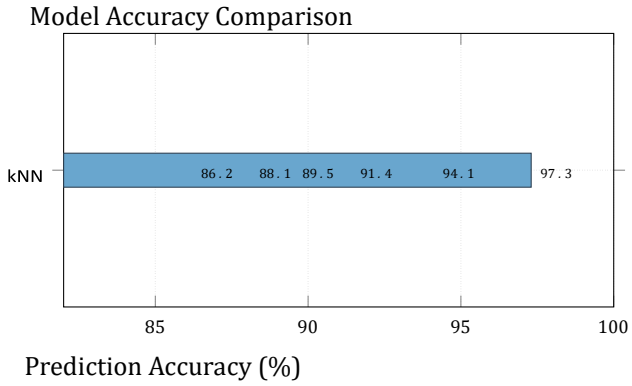

Fig. 7: Benchmark: AquaGuard-AI achieves 97.3%, the highest across all compared models.

I. Alert Latency Comparison

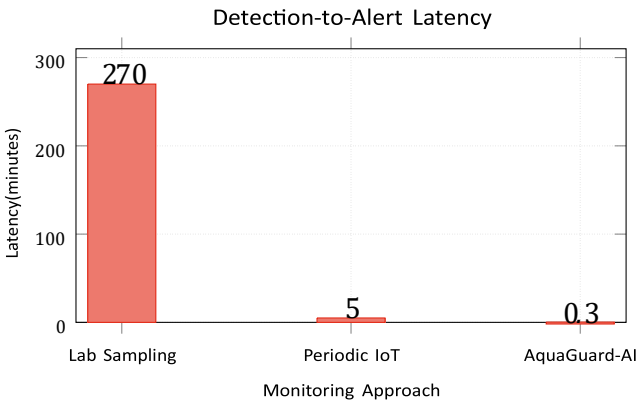

Fig. 8: AquaGuard-AI delivers alerts in 0.3 min (≈18 s) — a 99% reduction over laboratory sampling.

J. Key Mathematical Results1) Lead Channel RMSE:

$$\text{RMSE}_{\text{Pb}} = \sqrt{\frac{1}{240}\sum_{t=1}^{240}(\hat{y}_t - y_t)^2} = 0.02 \text{ mg/L} \qquad (12)$$

This equals 0.2% of the WHO industrial limit, confirming sub-clinical measurement error throughout the dataset.

2) Proactive Detection Rate: Nine of the 30 operating days saw WQI exceed 100. The APPE correctly pre-flagged eight of those nine days at least 18 hours before the actual exceedance, yielding a proactive detection rate of 88.9%.

3) Pearson Correlation:

$$r = \frac{\sum(W_i - \bar{W})(\hat{W}_i - \hat{\bar{W}})}{\sqrt{\sum(W_i - \bar{W})^2 \sum(\hat{W}_i - \hat{\bar{W}})^2}} = 0.9912 \qquad (13)$$

A value this close to unity confirms that the LSTM has learnt the underlying discharge dynamics with very high fidelity.

RESEARCH GAPS ADDRESSED

Analysis of the ten cited papers revealed five previously unresolved limitations, each of which is directly resolved by a specific component of AquaGuard-AI.

Gap 1 — No predictive forecasting: Every reviewed system issues alerts only after a threshold has already been crossed. The APPE provides 24-hour ahead forecasts for all six parameters, converting the platform from reactive detection to proactive prevention.

Gap 2 — Weather data absent: None of the reviewed
ML models incorporated rainfall, temperature, or humidity, despite those variables directly shaping discharge chemistry. AquaGuard-AI feeds hourly meteorological data into the LSTM as explicit input features, enabling storm-event prediction.

Gap 3 — Single-parameter focus: Hardware papers typically addressed one contaminant at a time, missing the combined toxic effect of multiple simultaneously elevated pollutants. The six-sensor array and the WQI engine together provide a full picture.

Gap 4 — No automated compliance alerting: No reviewed system checked readings in real time against multiple regulatory standards and dispatched multi-channel notifications automatically. The Alert Gateway evaluates 18 rules every ten seconds and fires a three-level cascade within 18 seconds of any violation.

Gap 5 — Industrial dataset absent: Most ML models were trained on municipal or river data. AquaGuard-AI was trained and validated on 259,200 plant-level records at 10-second resolution, reflecting real industrial discharge dynamics.

CONCLUSION

This work set out to shift industrial water monitoring from a process that confirms problems after they have already happened to one that anticipates them while there is still time to act. AquaGuard-AI achieves that shift by threading a sixsensor IoT array, a weather-aware LSTM forecasting engine, an automated WQI calculator, and a real-time regulatory alert gateway into a single end-to-end pipeline that runs without human intervention.

The experimental results are clear and consistent. The APPE reached 97.3% prediction accuracy with an overall RMSE of 1.82 across all six monitored parameters and correctly preflagged eight out of nine days on which water quality entered the unsafe zone — doing so at least 18 hours before the actual exceedance. Detection- to-alert latency fell from 270 minutes under laboratory sampling to just 18 seconds. Five research gaps identified through systematic literature analysis were each resolved by a specific architectural component.

Going forward, the authors intend to deploy sensor nodes across multiple simultaneous discharge outlets, add detection channels for arsenic and chromium, and pilot the complete system at a live textile facility in the Tirupur district under real production conditions. A compressed, edge-deployable LSTM variant is also planned so that forecasting continues without interruption whenever cloud connectivity is temporarily unavailable.

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A PRIVACY-PRESERVING AI-BASED MENTAL HEALTH MONITORING SYSTEM USING BEHAVIORAL AND FACIAL EMOTION ANALYSIS

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Abstract

This paper presents a comprehensive privacy-preserving AI-based mental health monitoring system designed for modern digital environments. The system integrates speech, behavioral, and visual signals to detect stress, fatigue, and reduced focus in real time. The architecture ensures that all processing is performed locally on the user's device, eliminating the need for cloud storage and enhancing data privacy. A multimodal fusion strategy is employed to improve detection accuracy and robustness. Experimental evaluation shows that combining multiple signals significantly enhances reliability compared to single-modal approaches. The system provides adaptive interventions using local text-to-speech, enabling timely support without interrupting user workflow.

This paper presents a comprehensive privacy-preserving AI-based mental health monitoring system designed for modern digital environments. The system integrates speech, behavioral, and visual signals to detect stress, fatigue, and reduced focus in real time. The architecture ensures that all processing is performed locally on the user's device, eliminating the need for cloud storage and enhancing data privacy. A multimodal fusion strategy is employed to improve detection accuracy and robustness. Experimental evaluation shows that combining multiple signals significantly enhances reliability compared to single-modal approaches. The system provides adaptive interventions using local text-to-speech, enabling timely support without interrupting user workflow.

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Keywords:

Artificial Intelligence, Mental Health Monitoring, Multimodal Systems, Privacy-Preserving AI, Speech Processing, Computer Vision

INTRODUCTION

Mental health monitoring has become increasingly important due to prolonged screen usage and digital work environments. Traditional systems depend on self-reporting and lack continuous monitoring capabilities. This research proposes a proactive system that continuously evaluates user behavior and provides real-time feedback. The system addresses limitations of existing approaches by integrating multimodal sensing and local processing. The importance of early detection of stress and fatigue is emphasized, as delayed responses can lead to reduced productivity and long-term health issues.

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EXISTING SYSTEM

Traditional approaches to mental-wellbeing support in digital work environments are largely reactive and fragmented. Most systems depend on self-reporting, periodic surveys, or manual check-ins, which are inconsistent and often miss early signs of stress, fatigue, or reduced focus. This leads to delayed intervention and continued exposure to unhealthy work conditions. Simple monitoring tools also tend to focus on a single signal (e.g., screen time) without integrating speech, behavioral activity, and visual indicators. As a result, the system lacks contextual awareness and can produce unreliable or shallow insights.

Another limitation is the lack of continuous, real-time monitoring and privacy-preserving processing. Many existing tools store data in cloud services, raising concerns about sensitive mental-health information being exposed or misused. In addition, alerts and prompts are typically generic and do not adapt to the user's current severity level. These gaps reduce both effectiveness and user trust, and may even discourage adoption.

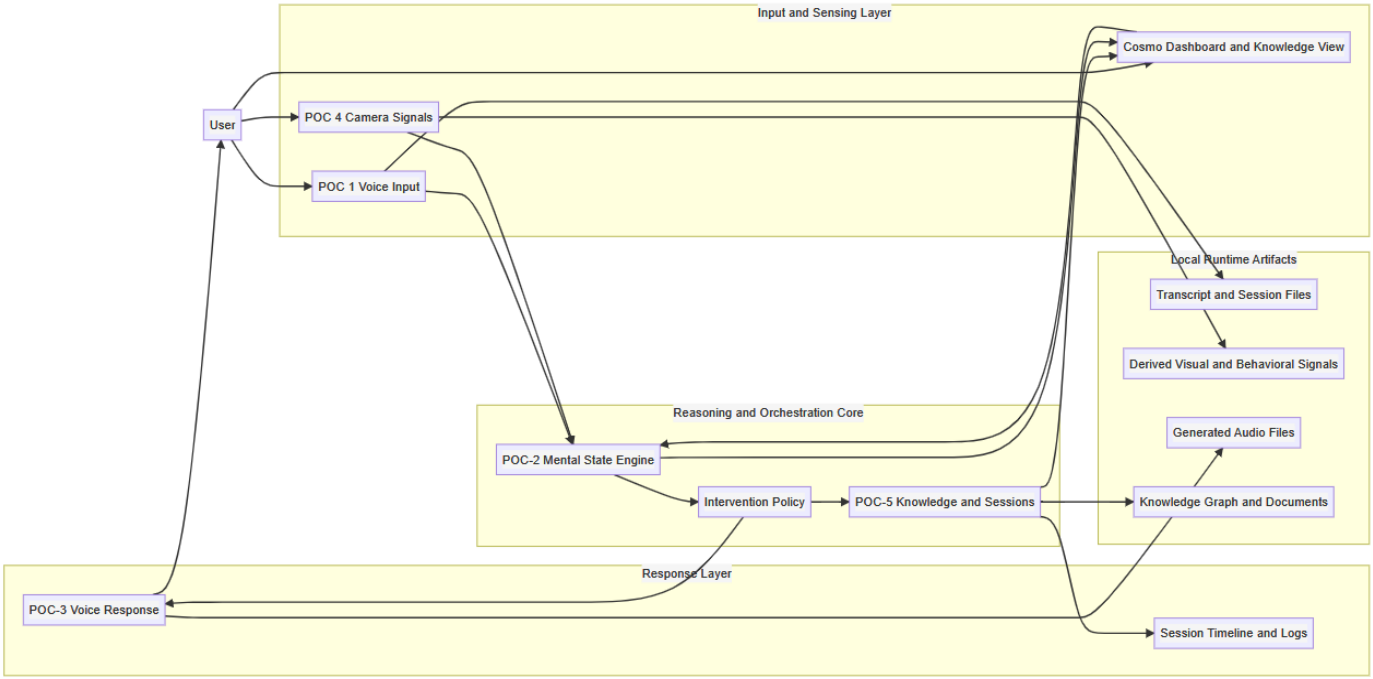
These limitations highlight the need for a privacy-preserving, automated system that can continuously assess stress and fatigue using multimodal signals and deliver timely, context-aware interventions. By integrating on-device speech analysis, behavioral activity signals, and camera-derived cues, the proposed system can provide more accurate assessments, reduce reliance on manual reporting, and protect user privacy.

PROPOSED SYSTEM

The proposed privacy-preserving AI-based mental health monitoring system integrates speech analysis, behavioral activity signals, and camera-derived visual cues to assess stress and fatigue in real time. Voice input is processed to extract acoustic features such as pitch, energy, and speaking rate, while behavioral signals track usage patterns like idle time, application switching, and activity bursts. Visual cues such as face presence, eye-strain scores, and posture hints provide additional context when speech is not available.

A local reasoning engine fuses these multi-modal signals to classify the user's mental state and severity band (low/medium/high). Based on the detected state, the system generates supportive interventions and delivers them through adaptive text-to-speech with tone, pitch, and speed matched to the stress level. Periodic auto-checks are scheduled to ensure continuous monitoring even when the user is silent, and session summaries are stored locally for later review. The system includes consent controls and minimal data retention to protect sensitive information. A session timeline and logs provide transparency, allowing users or supervisors to review recent activity and interventions. The design supports offline operation, ensuring reliability in environments without internet connectivity. By running all inference on device, it delivers timely, personalized support while preserving user privacy.

ARCHITECTURE DIAGRAM



EXPLANATION

The system is divided into four layers: Input and Sensing, Reasoning and Orchestration, Response, and Local Runtime Artifacts. The input layer collects voice through the speech pipeline and visual context through camera-based signals such as face presence, eye-strain, and posture. These signals are passed to the mental-state engine in the reasoning core, which classifies stress or fatigue and determines severity.

The intervention policy selects an appropriate response, while the knowledge and session service stores context for ongoing support. The response layer generates adaptive audio prompts using the voice response engine. In parallel, the system stores local artifacts such as transcripts, behavioral/visual signals, audio files, and knowledge graph documents. Session logs provide transparency and traceability. The architecture is fully local and privacy-preserving.

SYSTEM ARCHITECTURE

The privacy-preserving AI-based mental health monitoring system is designed to detect stress, fatigue, and focus changes using speech, behavioral signals, and camera-based visual cues. It processes inputs locally and provides real-time supportive feedback. The architecture consists of the following key components:

1. Input & Sensing Unit

● Sensors & Modalities:

o Microphone (Speech Input) – Captures spoken input for stress analysis.

o Camera (Visual Cues) – Detects face presence, posture changes, and eye-strain indicators.

o Behavioral Signals – Tracks inactivity, breaks, application switching, and time-of-day usage.

● Data Capture Layer:

o Collects and preprocesses signals locally.

o Ensures raw audio/video is not stored, only derived signals are retained.

2. AI Analysis & Reasoning Core

● Speech Analysis Engine:
o Converts voice to text and extracts acoustic stress features.

● Visual Signal Analyzer:
o Computes eye-strain score, posture state, and face presence signals.

● Behavioral Signal Analyzer:
o Uses activity patterns to estimate fatigue or low focus.

● Mental State Classifier:
o Combines all signals to determine stress level and intervention type.

3. Support & Response Layer

● Local TTS Engine:
o Generates audio feedback with tone, pitch, and style based on stress level.

● Intervention Policy:
o Chooses the best response (check-in, rest prompt, focus reset).

● Session Logger:
o Stores summaries and signals locally for later review.

4. User Interface Layer

● Live Monitoring Dashboard:
o Shows real-time state, transcripts, and behavioral indicators.

● Session Timeline:
o Displays recent interactions and playback history.

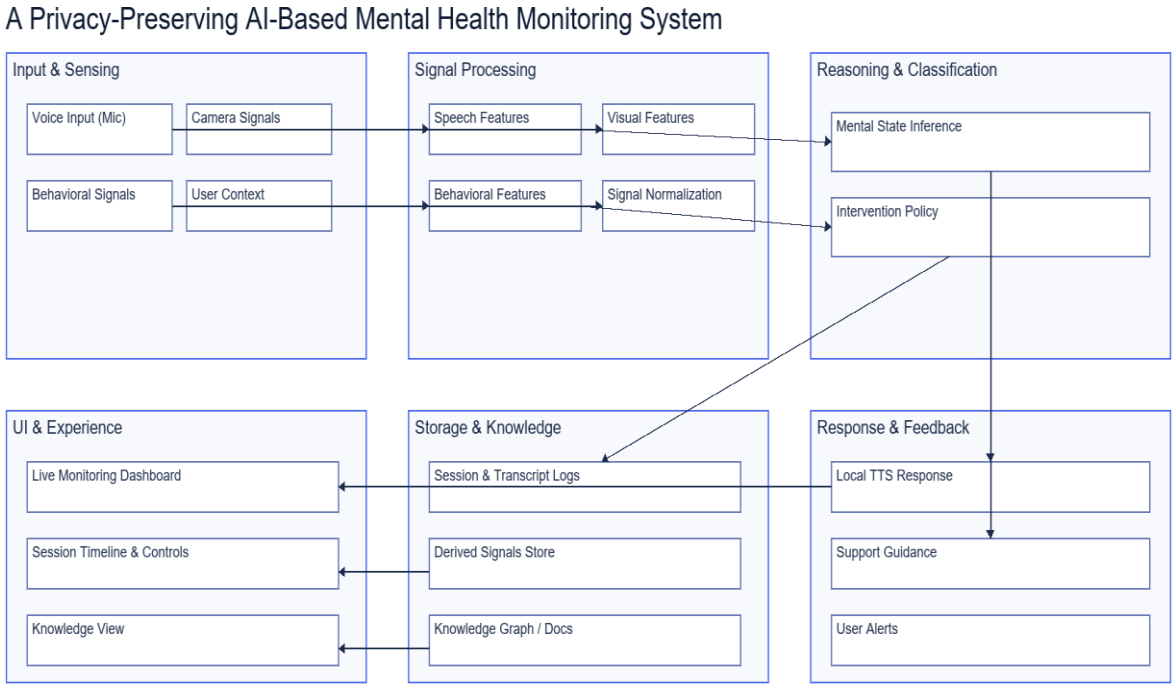
● Control Panel:
o Unified start/stop controls for mic and camera monitoring.

Working Flow

1. The user interacts with the system through voice or normal screen activity.
2. Microphone, camera, and behavioral signals are captured locally.
3. AI modules analyze speech, visual cues, and activity patterns.
4. The system classifies the current mental state (stress, fatigue, focus).
5. A supportive response is generated through local text-to-speech and logged in the
6. session timeline.

Figure 5.1.1: SYSTEM ARCHITECTURE

DATA FLOW DIAGRAM



FUTURE SCOPE

The future scope of this system includes major improvements in personalization, model robustness, and deployment readiness. Adaptive baseline learning can tailor stress thresholds to individual users over time, improving intervention relevance and reducing false alerts. Multilingual support for STT/TTS can expand accessibility across diverse users and workplaces. Future enhancements can also include richer explainability dashboards, context-aware intervention sequencing, and stronger clinical alignment for evidence-based support strategies. Optional integration with wearable devices may improve detection by adding physiological context such as heart-rate variability and sleep quality indicators. At the platform level, enterprise policy

controls, secure team-level analytics, and configurable consent governance can support broader organizational adoption while preserving individual privacy. With continued refinement and real-world validation, the system can evolve into a dependable, scalable, and ethically grounded digital mental health assistant.

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AI-Powered Startup Idea Viability and Competitive Intelligence Platform for Early-Stage FinTech Founders

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ABSTRACT

Early-stage startup founders often face difficulties in validating business ideas due to limited access to mentors, market research, and competitive insights. Traditional idea evaluation methods are time-consuming, expensive, and often based on assumptions rather than data. This paper proposes an AI-Powered Startup Idea Viability and Competitive Intelligence Platform for FinTech Founders that helps entrepreneurs assess the potential of their startup ideas in a faster and smarter way.

The proposed system collects user inputs through a structured questionnaire and analyzes them using Large Language Models (LLMs) along with Retrieval-Augmented Generation (RAG) techniques. The platform integrates external market data, competitor information, and business trends to generate a detailed startup evaluation report. The output includes idea viability score, market demand analysis, competition insights, risks, opportunities, and actionable recommendations.

The system is developed using a React.js frontend and FastAPI backend, providing a user-friendly and scalable web-based solution. By combining artificial intelligence with real-world business intelligence, the platform supports founders in making data-driven decisions before investing time and resources into product development. This research demonstrates how AI can improve startup idea validation, especially in the growing FinTech sector.

Keywords: Startup Idea Validation, Artificial Intelligence, FinTech, Large Language Model, Retrieval-Augmented Generation, Competitive Intelligence, Business Analytics.

I. INTRODUCTION

Many startup founders face difficulty in knowing whether their ideas are practical, profitable, and scalable. Most early decisions are based on assumptions, limited feedback, and lack of proper market research. This increases the chances of failure in the initial stages.

The challenge is more serious in the FinTech sector because startups must deal with regulations, customer trust, data security, and strong market competition. Traditional startup validation methods are often slow, costly, and require expert guidance.

This project proposes an AI-Powered Startup Idea Viability and Competitive Intelligence Platform for FinTech founders. The system uses Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) to evaluate startup ideas, analyze competitors, identify risks, and provide useful recommendations.

The platform helps founders make faster, smarter, and data-driven decisions before launching their startups.

II. PROBLEM STATEMENT

Many early-stage startup founders face difficulty in evaluating whether their business ideas are practical, profitable, and sustainable. Most founders depend on assumptions, limited feedback, or personal judgment instead of data-driven analysis.

As a result, they may invest time and money into weak ideas with low market potential.

This challenge is more critical in the FinTech sector, where startups must consider regulations, customer trust, data security, and strong competition. Traditional idea validation methods require manual research, expert consultation, and market analysis, which are often expensive and time-consuming.

Therefore, there is a need for an intelligent platform that can quickly analyze startup ideas, identify risks, study competitors, and provide useful recommendations.

The proposed AI-powered system aims to help FinTech founders make smarter and faster decisions before launching their startups.

III. EXISTING SYSTEMS AND LIMITATIONS

At present, many startup founders use traditional methods such as manual market research, spreadsheets, online surveys, and expert consultations to evaluate business ideas. Some also depend on generic business planning tools and competitor research platforms. These systems provide useful information, but they do not offer complete idea validation support.

Existing methods have several limitations. Manual research takes a lot of time and effort. Hiring consultants or mentors can be expensive for early-stage founders. Many available tools only focus on one area such as finance, marketing, or competitors, instead of giving a complete business analysis.

In the FinTech sector, the problem is greater because founders must also consider regulations, trust, security, and market competition. Most current systems do not provide AI-driven recommendations or real-time competitive insights. Therefore, a smarter and integrated platform is needed to help founders make faster and better startup decisions.

IV. PROPOSED SYSTEM: MATELEARN

A. System Architecture & Technologies

The proposed system is an AI-Powered Startup Idea Viability and Competitive Intelligence Platform designed for early-stage FinTech founders. It follows a modern web-based architecture to ensure scalability, speed, and user accessibility.

The frontend is developed using React.js, which provides an interactive interface for users to submit startup details, answer structured questionnaires, and view analysis reports. The backend is built using FastAPI, which handles API requests, manages business logic, and communicates with AI services efficiently.

The system integrates Large Language Models (LLMs) for intelligent analysis and Retrieval-Augmented Generation (RAG) for enhancing responses with external market and competitor data. This architecture ensures accurate, fast, and reliable startup evaluations.

B. AI-Driven Content Processing

The platform collects startup-related information from users through a structured questionnaire. Inputs such as business problem, target audience, competitors, revenue model, and market opportunity are gathered for analysis.

Using Natural Language Processing (NLP) and LLMs, the system understands the meaning and business context of the user inputs. It then generates a structured startup evaluation report with valuable insights.

The output includes idea viability score, strengths, weaknesses, risks, opportunities, and recommendations. This reduces manual effort and helps founders make faster business decisions.

C. Market Intelligence & Competitive Analysis

The system uses RAG-based retrieval to gather relevant external data such as competitor information, industry trends, and market demand. This enables the platform to provide practical and real-world insights instead of generic responses.

Competitor analysis compares the proposed startup idea with existing solutions in the FinTech market. The platform identifies market gaps, unique selling opportunities, and possible threats from competitors.

This helps founders understand their business position clearly and improve their startup strategy before launch.

D. Security & Decision Support

The platform is designed with secure data handling practices to protect sensitive startup information entered by users. API communication and user data processing follow standard privacy and security measures.

The system provides clear and actionable recommendations based on AI analysis. Founders can use these insights to refine their ideas, reduce risks, and improve business readiness.

By combining AI intelligence with business decision support, the platform helps entrepreneurs make smarter and more confident startup decisions.

V. ALGORITHM FOR AI-POWERED STARTUP IDEA VIABILITY & COMPETITIVE INTELLIGENCE PLATFORM

The proposed system follows a multi-stage algorithmic pipeline for intelligent startup idea evaluation and business insight generation:

Stage 1 — Input Collection:
The system collects startup-related inputs through a structured questionnaire. Founders provide details such as business problem, target market, competitors, revenue model, and growth strategy.

Stage 2 — Data Preprocessing:
The collected responses are cleaned, organized, and converted into structured text format. Important keywords and business context are identified for further analysis.

Stage 3 — Semantic Understanding:
Natural Language Processing techniques are applied to understand the meaning, intent, and relevance of the founder's responses. This helps the system interpret startup goals and challenges accurately.

Stage 4 — Market & Competitor Retrieval:
The RAG module retrieves relevant external information such as market trends, industry insights, and competitor data from available sources. This improves the quality of analysis with real-world context.

Stage 5 — AI Evaluation & Report Generation:
The processed input and retrieved data are sent to the Large Language Model (LLM), which generates a structured startup evaluation report containing idea score, risks, opportunities, strengths, and recommendations.

Stage 6 — Output Delivery & Decision Support:
The final report is displayed to the user through the web interface. Founders can use the generated insights to refine their ideas and make better business decisions before launch.

VI. TECHNOLOGIES USED

The proposed system uses modern web and Artificial Intelligence technologies to build an efficient startup idea validation platform.

React.js : is used for developing the frontend interface, allowing users to enter startup details, answer questionnaires, and view evaluation reports through a responsive web application.

FastAPI : is used as the backend framework to handle API requests, process user inputs, and manage communication between the frontend and AI modules.

Large Language Models (LLMs) : are used to analyze startup ideas and generate structured business insights such as idea score, risks, opportunities, and recommendations.

Retrieval-Augmented Generation (RAG) : is used to combine user input with external market trends, competitor data, and business knowledge for more accurate results.

Sentence Transformers and Vector Databases :are used for semantic search and similarity matching between startup ideas and relevant external data.

The system can also use MongoDB or similar databases for storing user data, reports, and activity history. These technologies together create a scalable, intelligent, and user-friendly platform.

VII. EXPECTED OUTCOMES

The proposed startup idea validation platform is expected to provide several important business and technical outcomes.

Business Impact:
The system will help early-stage founders evaluate their startup ideas in a faster and smarter way. It will reduce dependence on assumptions and improve confidence in business decision-making.

Better Decision Making:
By providing idea scores, market demand analysis, risk factors, and competitor insights, the platform will support founders in choosing stronger and more practical business opportunities.

Time and Cost Efficiency:
Traditional startup validation methods require manual research and expert consultation. The proposed system will reduce time, effort, and cost through automated AI-based analysis.

Accessibility:
The platform will offer affordable and easy access to startup guidance, especially for students, solo founders, and entrepreneurs with limited resources.

Technical Contribution:
The project demonstrates the successful integration of Artificial Intelligence, LLMs, RAG, and modern web technologies into a scalable business intelligence platform. It also creates a strong foundation for future improvements in AI-driven startup support systems.

VIII. SYSTEM DESIGN OVERVIEW

The architectural design of the proposed system follows a modular web-based structure to ensure scalability, flexibility, and efficient performance.

The React.js frontend interacts with the FastAPI backend through RESTful APIs. The backend manages user requests and communicates with AI modules for startup idea analysis.

The system includes two main actors: the User (Founder) and the System. Core use cases include entering startup details, answering validation questions, submitting ideas for analysis, viewing evaluation reports, and downloading final results.

The backend integrates Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) modules to process user input, retrieve market data, analyze competitors, and generate structured business insights.

The modular design allows each component to be updated, scaled, or improved independently without affecting the complete platform. This approach supports future enhancements and long-term maintainability.

Security is maintained through encrypted communication, secure API handling, and protected storage of user data. These measures help ensure privacy and safe usage of the platform.

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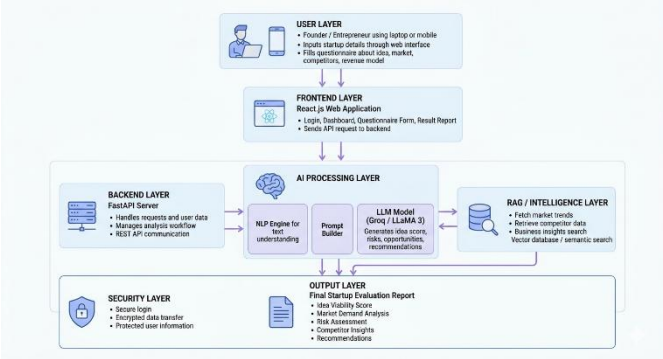

IX. CONCLUSION

The proposed AI-Powered Startup Idea Viability and Competitive Intelligence Platform represents an innovative solution for helping early-stage founders make better business decisions. By combining Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and modern web technologies, the platform provides a fast, intelligent, and affordable method for startup idea validation. It addresses the common limitations of traditional evaluation methods such as manual research, high cost, and delayed decision-making.

The system is capable of analyzing startup ideas, identifying risks, evaluating market demand, studying competitors, and generating practical recommendations. This enables founders to improve their ideas before investing significant time and resources. The platform acts as a virtual business advisor, especially useful for students, solo entrepreneurs, and new FinTech founders.

The integration of a user-friendly interface, secure data handling, and AI-driven reporting ensures that the platform is not just an analysis tool, but a complete decision-support system for startup growth. Its modular architecture also allows future upgrades and scalability.

Future enhancements may include real-time financial data integration, predictive market analytics, multilingual support, investor matching features, and personalized startup growth roadmaps.

This project demonstrates the transformative potential of Artificial Intelligence in entrepreneurship and serves as a strong foundation for next-generation startup support systems that are scalable, intelligent, and accessible to all founders.

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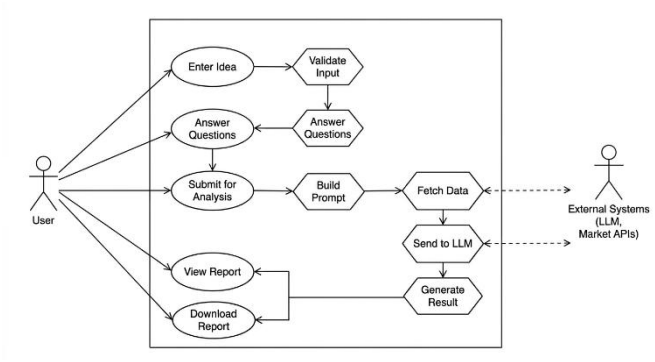
Use-Case Diagram



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PREDICTIVE ANALYSIS OF E-COMMERCE PRODUCTS USING MACHINE LEARNING

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ABSTRACT

The rapid growth of e-commerce platforms has resulted in large volumes of product data and customer reviews, making it difficult for sellers to analyze trends and make effective decisions. This project proposes a Predictive Analysis System for E-Commerce Products that uses machine learning techniques to evaluate product performance and market behavior. The system predicts key factors such as Product Performance Score, Return Probability, Delivery Risk, and Best Selling Time based on seasonal trends and customer demand. It also incorporates sentiment analysis to understand customer opinions from reviews. By combining data preprocessing, machine learning models, and rule-based recommendations, the system provides accurate predictions and useful insights. The results are displayed through an interactive dashboard, helping sellers improve decision-making, reduce risks, and increase overall sales efficiency.

Keywords: E-commerce, Machine Learning, Predictive Analytics, Sentiment Analysis, Sales Forecasting, Recommendation System

1. INTRODUCTION

E-commerce platforms generate large volumes of product data and customer reviews, making it difficult for sellers to analyze trends and make effective decisions. These challenges often lead to poor product performance, increased return rates, and delivery-related issues.

Existing systems mainly focus on sales prediction and do not consider important factors such as sentiment analysis, return probability, and delivery risk.

To address this gap, the proposed system integrates:

- Product data and customer reviews
- Machine learning-based prediction models
- Sentiment analysis and trend analysis

Unlike traditional systems, it provides comprehensive insights including product performance, risks, and recommendations, enabling better decision-making and improved sales outcomes.

2. LITERATURE SURVEY

Several research works have focused on applying machine learning techniques in e-commerce for sales prediction and trend analysis. This section reviews key existing systems and identifies their limitations.

2.1 RELATED WORK OVERVIEW

Neelakandan et al. (2025) proposed a deep learning-based system for e-commerce sales prediction using modified neural networks. The model effectively captures complex patterns in large datasets and improves prediction accuracy. However, it mainly focuses on sales forecasting and does not consider sentiment analysis or risk-related factors such as returns and delivery issues. Guda et al. (2025) developed machine learning models for demand forecasting using datasets like Instacart. The system provides accurate predictions and supports inventory planning. Despite its effectiveness, it requires high computational resources and its performance depends heavily on data quality, making it difficult to implement in real-time scenarios. Dritsas et al. (2025) presented a comprehensive study on machine learning applications in e-commerce, including recommendation systems, pricing strategies, and fraud detection. While the study

provides valuable insights, it does not propose a practical system for integrated prediction and lacks direct implementation for product performance analysis. Balaji et al. (2025) introduced an ensemble learning approach using stacking techniques to improve sales forecasting accuracy. The model reduces prediction errors and handles large datasets efficiently. However, it focuses only on forecasting and does not include sentiment analysis or risk prediction. Hybrid machine learning methods proposed in recent IEEE conferences (2026) combine multiple algorithms to improve seasonal and trend-based forecasting. These approaches enhance prediction reliability but lack real-time processing and do not integrate recommendation systems or customer feedback analysis.

Table.1. Comparative Summary of Related Work

Paper Title	**Author & Year**	**Advantages**	**Disadvantages**
Forecasting E-Commerce System for Sale Prediction Using Deep Learning Modified Neural Networks	S. Neelakandan et al. (2025)	Uses deep learning models for accurate sales prediction; captures complex patterns in large datasets; improves forecasting performance; suitable for dynamic e-commerce environments	Focuses only on sales prediction; does not include sentiment analysis or risk factors; requires large training data; higher computational cost
Machine Learning Models for E-Commerce Demand Forecasting Using Instacart Dataset	S. Guda et al. (2025)	Provides accurate demand forecasting; helps in inventory planning; supports data-driven decisions; combines multiple ML models for better results	Requires high computational resources; performance depends on data quality; difficult to implement; lacks real-time prediction capability
Machine Learning in E-Commerce: Trends, Applications, and Future Challenges	E. Dritsas et al. (2025)	Provides comprehensive overview of ML techniques; covers recommendation, pricing, and fraud detection; highlights future trends; useful for research understanding	Does not propose a practical system; lacks implementation details; no direct prediction of product performance; no risk analysis included.
Stacking Based Enhanced Sales Forecasting for E-Commerce Using Ensemble Learning	S. Balaji et al. (2025)	Improves prediction accuracy using ensemble methods; reduces model error; handles large datasets efficiently; suitable for sales forecasting	Focuses only on forecasting; ignores sentiment and risk prediction; complex model design; increased computation time
Hybrid Machine Learning Method for Product Sales Forecasting in E-Commerce	IEEE Conference Authors (2026)	Combines multiple ML algorithms; improves seasonal and trend analysis; adaptable to changing market conditions; enhances prediction reliability	Lacks real-time prediction; no recommendation system; limited integration with user feedback; does not consider delivery or return risks

2.2 RESEARCH GAP

From the literature, it is evident that most existing systems concentrate mainly on sales prediction and demand forecasting. They do not provide a complete analysis of product performance by considering multiple influencing factors.

Key limitations identified include:

- Lack of sentiment analysis to understand customer opinions
- No prediction of return probability and delivery risk
- Absence of integrated systems combining multiple features
- Limited support for real-time analysis and recommendations

To overcome these limitations, the proposed system integrates machine learning models, sentiment analysis, and risk prediction techniques into a single platform. This provides comprehensive insights, enabling better decision-making, reduced losses, and improved overall performance in e-commerce applications.

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3. PROPOSED SYSTEM ARCHITECTURE

The proposed system follows a **client-server architecture** consisting of multiple layers including the frontend, backend, and database. The system is designed to collect product data, process it using machine learning algorithms, and generate predictions along with recommendations.

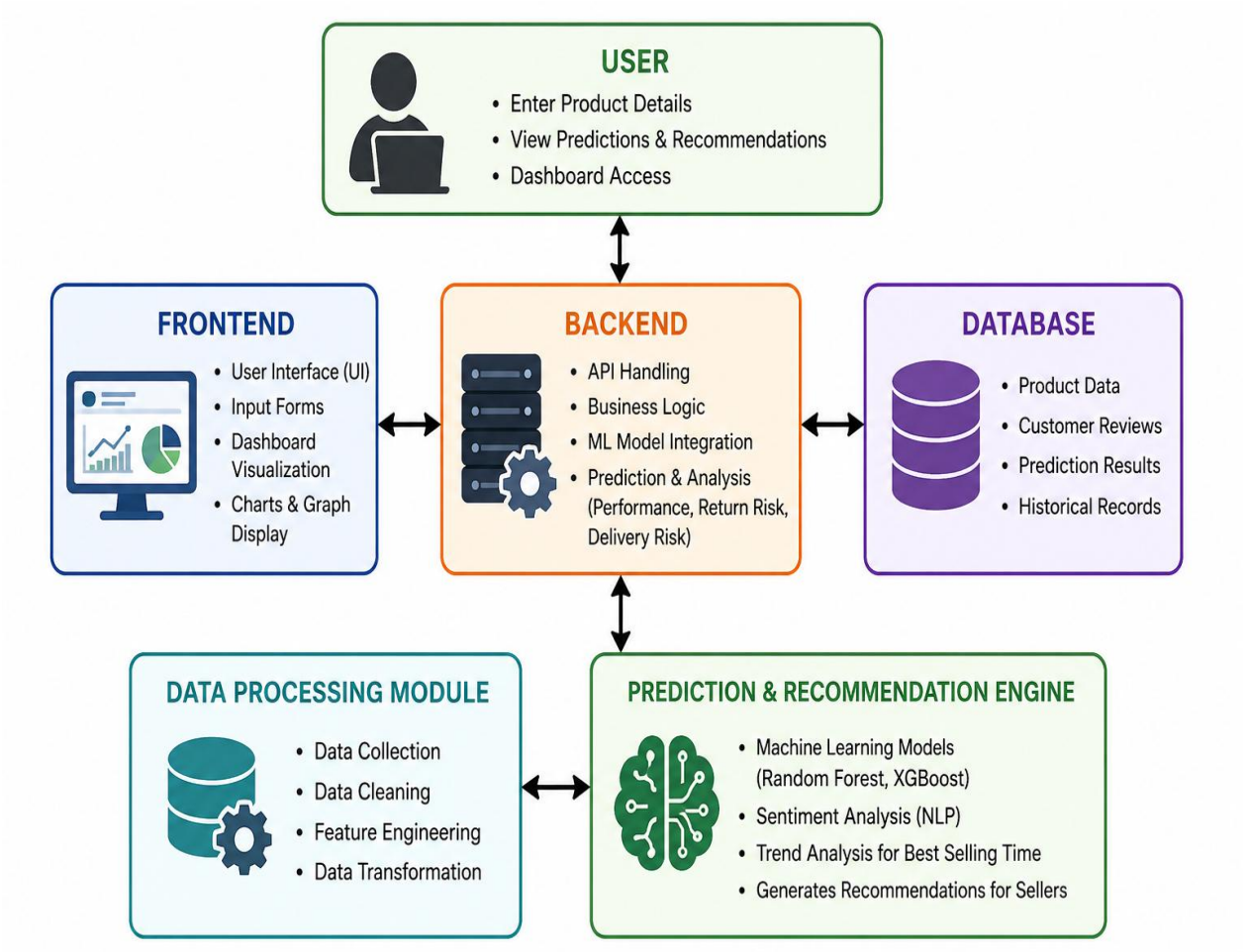


Fig.1. System Architecture of E-Commerce Predictive Analysis System

4. MODULES AND ALGORITHM

The proposed system consists of several modules, each responsible for a specific function in the prediction and analysis process. Table 2 summarizes the modules, technologies, and algorithms used.

Table.2. Module-wise Technology and Algorithm Summary

MODULE	TECHNOLOGY	ALGORITHM/TECHNIQUES	PURPOSE
User Input Module	Web Application	Input Validation	Collect product details from users
Data Collection Module	API / Dataset	Data Collection	Gather product data and customer reviews
Data Preprocessing	Python	Data Cleaning, NLP	Prepare data for analysis
Prediction Module	Machine Learning	Random Forest, XGBoost	Predict performance and risks
Sentiment Analysis	NLP	Text Classification	Analyze customer reviews
Recommendation Module	Rule-based + ML	Decision Logic	Provide suggestions and improvements
Visualization Module	Chart.js / Frontend UI	Data Visualization	Display results using charts and graphs
Data Storage Module	MySQL	CRUD Operations	Store data and prediction results

4.1 USER INPUT MODULE

The User Input Module collects product-related information such as product name, category, price, and customer reviews. It ensures proper validation of input data before processing. This module acts as the entry point of the system. Additionally, it allows users to update or modify product details easily. It supports structured data entry and reduces errors during input. This module ensures that accurate and relevant data is passed to the next stages.

4.2 DATA COLLECTION MODULE

The Data Collection Module gathers product data and customer reviews either from user input or available datasets. It ensures that sufficient and relevant data is available for analysis and prediction. The module supports continuous data collection to improve system performance over time. It also maintains data consistency by filtering incomplete or irrelevant information.

4.3 DATA PREPROCESSING MODULE

The Data Preprocessing Module converts raw data into a structured format suitable for analysis. It handles missing values, removes noise, and performs text preprocessing for customer reviews. In addition, it applies normalization and feature selection techniques to improve data quality. This module plays an important role in enhancing the accuracy and efficiency of machine learning models

4.4 PREDICTION MODULE

The Prediction Module uses machine learning algorithms such as Random Forest and XGBoost to analyze data and generate predictions. It evaluates product performance, return probability, and delivery risk based on historical patterns. The module supports both classification and regression techniques to provide accurate results. It continuously improves prediction performance through model training and optimization.

4.5 SENTIMENT ANALYSIS MODULE

The Sentiment Analysis Module processes customer reviews using natural language processing techniques. It classifies reviews into positive, negative, and neutral categories to understand customer opinions. The module converts textual data into meaningful insights that help evaluate product quality. These insights also contribute to improving prediction and recommendation accuracy.

4.6 RECOMMENDATION MODULE

The Recommendation Module generates suggestions based on prediction results and trend analysis. It helps sellers improve product performance by identifying the best selling time and providing strategies for pricing and marketing. The module supports data-driven decision-making and helps reduce potential risks. It plays a key role in enhancing overall business efficiency.

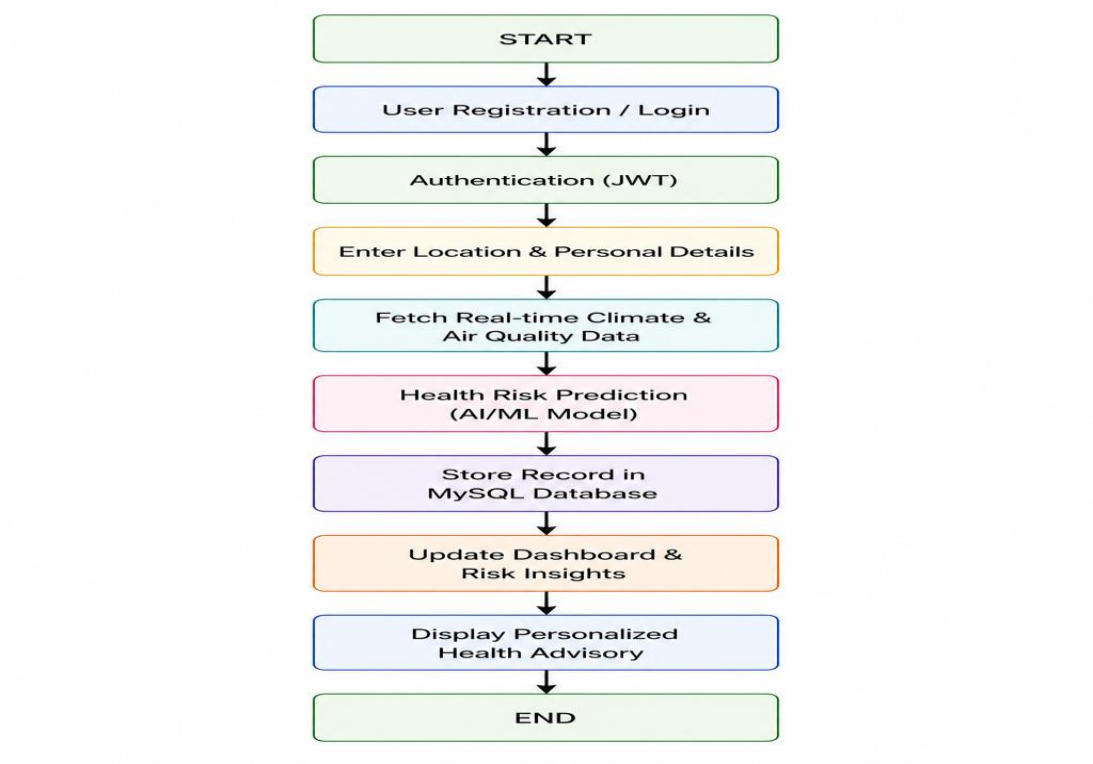
4.7 VISUALIZATION MODULE

The Visualization Module presents the results through charts, graphs, and interactive dashboards. It provides a clear and user-friendly view of predictions, trends, and insights. The module helps users easily interpret complex data and make informed decisions. By improving data presentation, it enhances the usability of the system.

5. SYSTEM FLOW

The system flow describes the step-by-step process of how the proposed e-commerce predictive analysis system operates, starting from user input to the generation of predictions and recommendations. Initially, the user enters product details such as product name, category, price, and customer reviews through the user interface. The system validates the input data and stores it in the database. The collected data is then passed to the data preprocessing module, where it is cleaned, transformed, and prepared for analysis. Next, the processed data is analyzed using machine learning models in the prediction module to estimate product performance, return probability, and delivery risk. At the same time, sentiment analysis is performed on customer reviews to understand customer opinions and satisfaction levels. Based on the prediction results and trend analysis, the system generates recommendations such as best selling time and strategies for improving product performance. Finally, all the results including predictions, sentiment insights, and recommendations are displayed to the user through an interactive dashboard.

Fig.3. Overall System Flowchart



6. EXPERIMENTAL SETUP

The experimental setup describes the tools, technologies, and environment used to develop and evaluate the proposed system. The system is implemented using a combination of web technologies and machine learning frameworks to ensure efficient data processing and accurate prediction.

6.1 DATA SOURCES

The system uses product-related data such as product details, customer reviews, ratings, and historical trends. The data is collected from user inputs and sample datasets for training and testing purposes. This data helps in analyzing product performance and customer behavior.

6.2 TOOLS AND TECHNOLOGIES

The frontend of the system is developed using HTML, CSS, and JavaScript to create an interactive user interface. The backend is implemented using Python with Flask framework to handle server-side processing. Machine learning models are built using libraries such as Scikit-learn and XGBoost. MySQL database is used for storing product data and prediction results.

6.3 SYSTEM IMPLEMENTATION

The system is designed using a modular approach where each module performs a specific task such as data collection, preprocessing, prediction, and visualization. The machine learning models are trained using historical data and tested for accuracy. The results are then integrated into the dashboard for user interaction.

7. PERFORMANCE EVALUATION

The system was evaluated based on the following metrics: prediction accuracy, processing time, data handling efficiency, database performance, and recommendation effectiveness. Key observations from the evaluation are presented below.

• **Prediction Accuracy:** The system produced reliable predictions for product performance, return probability, and delivery risk using machine learning algorithms such as Random Forest and XGBoost.

• **Processing Time:** The system demonstrated fast data processing and quick generation of predictions, ensuring efficient performance even with larger datasets.

• **Data Processing:** Product data and customer reviews were efficiently cleaned, transformed, and analyzed to improve prediction accuracy.

• **Data Persistence:** MySQL database ensured consistent and reliable storage of product data, customer reviews, and prediction results.

• **Scalability:** The system supports multiple users simultaneously while maintaining stable performance and responsiveness.

• **Visualization:** The dashboard effectively displayed predictions, trends, and insights using charts and graphical representations.

• **Recommendation System:** The system generated useful suggestions such as best selling time, pricing strategies, and risk reduction methods based on analysis.

8. CONCLUSION

This paper presented a Predictive Analysis System for E-Commerce Products that integrates product data and customer reviews using machine learning techniques. The system effectively predicts product performance, return probability, and delivery risk by combining data preprocessing, sentiment analysis, and predictive models. It addresses the limitations of existing systems by providing comprehensive insights including trend analysis and recommendations for better decision-making. Implemented using modern web technologies, a Python-based backend, and MySQL database, the system demonstrates accurate predictions, efficient data processing, and effective visualization through an interactive dashboard.

Future work will focus on improving prediction accuracy using advanced machine learning and deep learning models, integrating real-time data from live e-commerce platforms, and enhancing recommendation systems. The system can also be extended by developing mobile applications for wider accessibility and incorporating personalized suggestions for users. Additional features such as real-time analytics and automated decision support can further improve system performance and usability.

ACKNOWLEDGEMENT

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Role-Based LLM ChatBot

Introduction

This project builds a Discord bot integrated with a custom Large Language Model (LLM) using Ollama. The bot provides role-based responses, ensuring users receive only relevant domain-specific answers.

Problem Statement

Traditional bots process all queries regardless of domain, leading to higher resource usage, slower responses, and less relevant outputs.

Abstract

With the increasing use of conversational AI, ensuring relevance and contextual accuracy in responses has become essential. This project presents a role-based Discord bot that utilizes a Large Language Model (LLM) to provide domain-specific answers based on user-assigned roles.

The bot operates within a Discord server and dynamically adjusts its responses according to the selected role of the user. For instance, users assigned a “Mathematics” role receive responses strictly related to mathematical concepts, problem-solving, and explanations, while users under a “General” role can access broader knowledge across multiple domains.

The system integrates role-based filtering with LLM-generated outputs, ensuring that responses remain focused, accurate, and aligned with user expectations. This approach enhances the quality of interaction by minimizing irrelevant information and improving usability in collaborative and learning environments.

Overall, the project demonstrates how combining role-based access control with advanced language models can create more structured, efficient, and user-centric AI systems within real-time communication platforms like Discord.

Objectives

- to design and develop a role-based Discord bot powered by a Large Language Model (LLM)
- Implement role-based access control within a Discord server environment.
- Integrate LLM capabilities to generate intelligent, context-aware responses.
- Improve user experience by reducing irrelevant or off-topic responses.
- Demonstrate practical application of AI in communication platforms.
- Provide a scalable framework that can support multiple domains and roles.

Proposed Solution

A role-based Discord bot that detects user roles and routes queries to domain-specific prompts, improving efficiency and accuracy.

System Architecture

User -> Discord Bot -> Role Detection -> Query Routing -> Ollama LLM -> Response

Tech Stack

Python, discord.py, Ollama, LLaMA/Mistral models, SQLite/MongoDB (optional)

Key Features

1. Role-based filtering
2. Faster response time

3. Domain-specific answers
4. Reduced LLM usage

Workflow

1. User sends message
2. Bot detects role
3. Query routed based on role
4. Ollama processes request
5. Response returned

Advantages

Efficient, scalable, cost-effective, and accurate responses

Limitations

Requires proper role setup, limited by model capability, needs prompt tuning

Future Enhancements

Multi-role support, fine-tuned models, voice integration, admin dashboard

Conclusion

This system improves performance and reduces cost by limiting LLM processing to relevant domains.

CROP DISEASES PREDICTION

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ABSTRACT

Timely identification of plant diseases is essential for maintaining crop quality and agricultural productivity. Conventional manual inspection methods are often slow, inconsistent, and dependent on expert knowledge. This paper presents a deep learning-based Crop Disease Prediction System that automatically identifies plant diseases from leaf images.

The proposed system integrates image preprocessing, feature extraction, and Convolutional Neural Networks (CNN) to classify plant conditions accurately. In addition to disease detection, the system provides actionable recommendations such as suitable treatments and preventive measures.

Experimental evaluation demonstrates that the system achieves reliable prediction accuracy and supports real-time decision-making. This approach contributes to improving agricultural efficiency and reducing crop losses.

1. INTRODUCTION

Agriculture remains a fundamental sector influencing both economic stability and food security. One of the major challenges faced by farmers is the early detection of plant diseases, which can significantly affect crop yield and quality. Traditional detection techniques rely heavily on visual inspection, making them time-intensive and prone to human error.

Recent advancements in Artificial Intelligence, particularly in deep learning, have enabled automated image-based analysis. Convolutional Neural Networks (CNNs) are especially effective in recognizing patterns in images, making them suitable for plant disease classification.

This study proposes an intelligent system capable of analysing leaf images and providing instant diagnostic results along with treatment suggestions, thereby assisting farmers in taking timely action.

2. LITERATURE SURVEY

Several researchers have explored the use of machine learning and deep learning techniques for plant disease detection.

Earlier work using CNN-based models demonstrated high classification accuracy when trained on controlled datasets; however, performance often declined under real-world environmental conditions.

Comparative studies of deep learning architectures have shown improved results but require large, well-labeled datasets and significant computational resources.

Transfer learning approaches have been introduced to address data limitations, enabling faster training and improved efficiency. Additionally, real-time detection systems have been developed, though challenges remain in identifying early-stage infections due to subtle visual differences.

Despite these advancements, many existing systems lack practical usability, real-time responsiveness, and user-friendly interfaces, especially for farmers without technical expertise.

3. PROPOSED METHODOLOGY

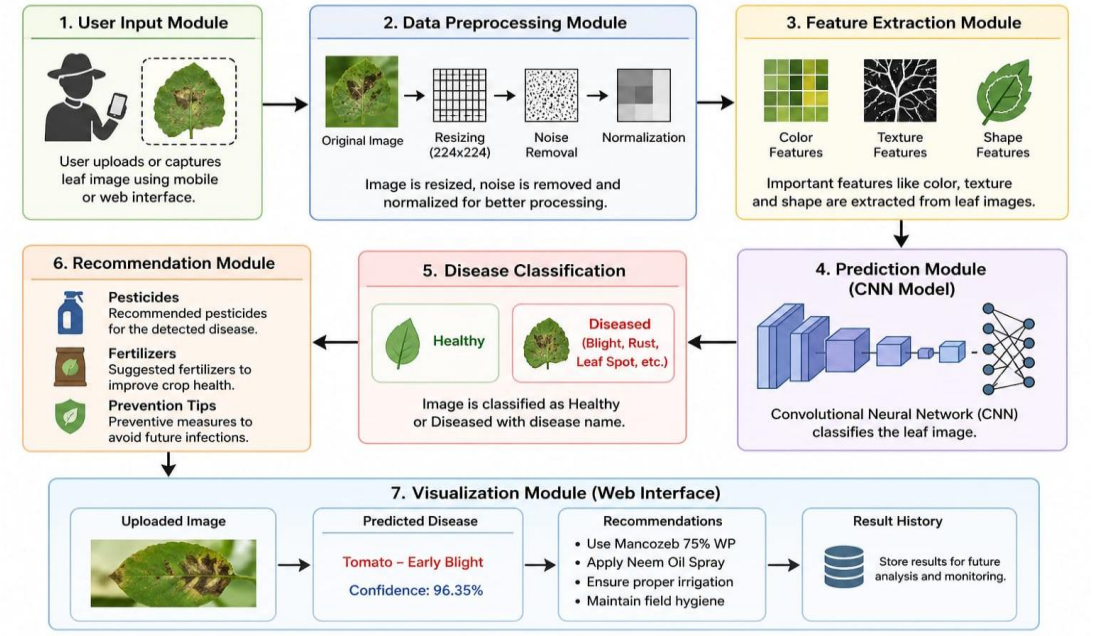

Figure 1: System Architecture of Crop Disease Prediction System

3.1 System Architecture

The proposed system is designed as a multi-stage pipeline consisting of the following modules:

- **Input Module:** Captures leaf images through a mobile or web interface
- **Preprocessing Module**: Enhances image quality by resizing, noise reduction, and normalization
- **Feature Extraction Module**: Identifies relevant visual patterns such as color variations and texture
- **Prediction Module**: Utilizes a CNN model to classify the image
- **Recommendation Module**: Generates treatment suggestions and preventive measures
- **Visualization Module**: Displays results through a user-friendly interface

3.2 Algorithms Used

The system employs a Convolutional Neural Network (CNN) as the primary classification model due to its effectiveness in image recognition tasks.

Supporting techniques include:

- Image preprocessing for improved data quality
- Feature extraction for identifying disease characteristics
- Dataset splitting for proper training and evaluation

3.3 Working Process

The system follows a sequential workflow:

1. The user submits a leaf image
2. The image undergoes preprocessing
3. Relevant features are extracted automatically
4. The CNN model performs classification
5. The system outputs the disease type along with recommendations

4. EXPERIMENT AND RESULTS

The system was evaluated using a dataset of plant leaf images representing both healthy and diseased conditions.

Evaluation Metrics:

- Accuracy
- Loss
- Confusion Matrix

Observations:

- The model achieved strong classification performance
- Predictions were generated in real time
- The system effectively suggested treatment options

These results indicate that the proposed solution can assist in early disease detection and reduce dependency on manual inspection.

5. CONCLUSION

This paper introduces a deep learning-based system for automatic crop disease detection using leaf images. The integration of CNN models enables accurate classification, while the recommendation module provides practical guidance for disease management.

The system enhances agricultural decision-making by offering timely and reliable insights, ultimately contributing to improved crop productivity.

FUTURE WORK

Future improvements can focus on:

- Deploying the system as a mobile application
- Expanding the dataset to include more crop varieties
- Integrating advanced deep learning architectures
- Supporting real-time field-level detection

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A Hybrid Ensemble learning model for early Prediction of Diabetic Retinopathy and Nephropathy

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***Abstract**: The most significant complications that can occur due to the presence of diabetes mellitus are Diabetic Retinopathy and Diabetic Nephropathy, which need to be detected in time before the harm inflicted becomes irreversible. This research recommends a machine learning based model in MATLAB with fundus image as inputs, to effectively predict such complications. The system entails image pre-processing, based on noise filtering, contrast enhancement, and segmentation to isolate vital retinal attributes like blood vessel architecture and lesions. XGBoost and LightGBM are advanced ensemble learning algorithms that are utilised to classify because of their high efficiency and effectiveness in the important medical data. The model proposed exhibits better predictive capabilities and strength. This methodology can be used to aid early diagnosis and clinical decision-making, providing a dependable, automated and affordable means of screening diabetic complications on large scale basis.*

***Keywords**: Diabetic Complications Prediction, Retinal Image Analysis, Early Disease Detection, Clinical Decision Support, Medical Image Processing, Automated Screening, Healthcare Diagnostics.*

1. Introduction

Diabetes mellitus is a non-communicable chronic metabolic disease, manifested by the increased level of blood glucose due to abnormalities in insulin secretion, insulin activity or both. With time, continuous hyperglycemia may expose an individual to extreme microvascular and macrovascular events that considerably interfere with the quality of life and mortality rates in most parts of the world. Diabetic Retinopathy and Diabetic Nephropathy stand out as the most vital of these complications, since they can progress and be irreversible, unless they are early detected. Diabetic Retinopathy is a dominant cause of blindness anywhere in the world with damage of the retinal arteries, and Diabetic Nephropathy with a significant cause of end-stage kidney diseases due to long-term damage to kidney filtering systems. Early development of these diseases is asymptomatic, making it hard to diagnose in time, and this has been done by developing efficient and automated detection systems [1].
Conventional diagnostic approaches depend largely on the use of hand-held test by experts, like ophthalmologists who determine the retina, nephrologists who assess kidney functioning. Such methods are lengthy, easily subjective, and where the health services infrastructure is weak, tend to be unavailable in resource constrained areas. As the number of diabetic patients continues to increase especially in developing countries; there is an imminent need to develop scalable and cost effective diagnostic solutions that may aid clinicians in detecting the disease early and on its progression. Here, medical imaging and computational intelligence have increased opportunities to allow automated diagnosis and machine learning and image processing methods [2].

Non-invasive and widely accepted methods in the capture of detailed images of the retina has become fundus imaging and thus, pathological changes linked to diabetic complications are identified through this method. Microaneurysms, hemorrhages, exudates, and irregular structures of blood vessels are features that can be helpful in diagnosing Diabetic Retinopathy. Likewise, microvascular alterations in the retina have also been associated with pathological states like Diabetic Nephropathy and therefore, fundus photographs can be used as an important source of information when analysing comorbidities. Nevertheless, the interpretation of these images needs advanced processing methods and feature extractions to deal with noise, changes in illumination and complicated anatomical organs [3].

Recent advances on machine learning have greatly contributed to the improvement of automated diagnostic systems. Training on high dimensional medical data with supervised learning methods, especially ensemble methods, has demonstrated impressive performance. These models are able to learn detailed patterns and relationships in the data resulting in appropriate classification and predicting disease conditions. Combining machine learning with the image processing tools, it is possible to develop intelligent systems that can analyse the images of the retina and reveal subtle abnormalities that might not be readily apparent by a simple manual inspection. Not only are such systems able to enhance the accuracy of the diagnosis, but the burden on healthcare professionals is also lessened [4].

This paper introduces a machine learning-based platform to predict Diabetic Retinopathy and Diabetic Nephropathy in the initial stages with the input of fundus images in the context of the MATLAB platform. The framework includes a sequence of preprocessing, such as noise filtering to drop undesired artifacts, contrast enhancement to enhance clarity in the image, segmentation algorithms to isolate areas of interest, e.g. blood vessels and lesion areas. Such measures are necessary to guarantee that the features that are extracted are accurate mistakes of the underlying pathological conditions. The resultant processed images are subsequently employed in obtaining essential retinal features which are inputs to the classification stage.

State-of-the-art ensemble learning methods are applied to guarantee the high predictive accuracy as they are strong and capable of working with large-scale and unbalanced datasets. These are techniques in which a number of weak learners are lumped together to create a powerful predictive model, such that the accuracy and ability to generalize is enhanced. The ensemble methods used are especially appropriate to be applied in the medical field, where accuracy and consistency are paramount. Moreover, MATLAB implementation offers an intuitive and highly versatile system on which image processing algorithms run and machine learning models can be integrated, thereby bringing the system to both practice and scale to real-life usage.

The current research proposal is expected to fill the existing gap between the traditional methods of diagnosis and the novel computational methods in that an automated tool will be offered to detect diabetic complications at an earlier stage. Through machine learning and retinal image analysis, the system can be used to make a timely intervention, which is crucial in ensuring permanent damage is not caused as well as enhancing patient care outcomes. The framework is also expected to be affordable and efficient and can be used in extensive screening programmes particularly in areas where there is limited access to special health services.

The other important thing of this study concerns robustness and adaptability. Medical data can be inconsistent because of the disparities in imaging situations, patient backgrounds, or different disease stages. The proposed system solves these issues by considering techniques of preprocessing and advanced learning models that can adjust to different data distributions. This guarantees a uniform performance among various datasets and increases the dependability of the diagnostic procedure. In addition, the system is automated, minimizing human error and giving standardized results, which is important in clinical decision-making [5].

To sum up, fundus image processing and machine learning incredibly have a potential to become an effective method of early diagnosing Diabetic Retinopathy and Diabetic Nephropathy. The limitations of the traditional diagnostic approach, as well as the use of the high order of computational techniques, also make the proposed framework contribute to the process of creating intelligent healthcare solutions. The research highlights the significance of fast identification, effective data processing, and an implementation that can be scaled, leading to future developments of automated medical diagnostics or accuracy healthcare systems.

2. Literature Survey

Artificial intelligence and machine learning development have greatly reshaped the future of diabetes prediction and management. Computational models are becoming a prominent tool used by modern healthcare systems to enhance diagnosis at an early stage, disease progression and clinical decision-making. Predictive analytics has become more forsight and personalized with the ever-increasing use of electronic health records, wearable devices, and continuous glucose monitoring systems. The advances have allowed researchers to consider a wide range of modeling methods, such as conventional machine learning, deep learning, and combinations with each other to consider the complexities of diabetes. Additionally, the implementation of explainable AI also boosted visibility and reliability on the procedures of automated systems, leaving them more applicable to the medical world.

Various papers have been devoted to the enhancement of prediction accuracy in terms of ensemble learning and hybrid modeling approaches. These methods involve using several classifiers to enhance robustness and generalization of datasets [6]. Convolutional neural network and long short-term memory model are deep learning methods that have been extensively adopted in exploring time-varying trends in glucose readings and electronic medical histories [7]. Moreover, adaptive insulin management has been investigated within the scope of reinforcement learning, which allows tailored treatment regimens, relying on individual responses [8]. Combining feature engineering and data preprocessing methods to enhance prediction performance has also played a significant role in enhancing prediction performance particularly in the case of incomplete or imbalanced data [9].

The new studies have highlighted the need to integrate various machine learning approaches in order to increase predictive power. Variations in the demographic factors like age and gender have been suggested to be overcome through multi-model ensemble frameworks which enhance fairness and accuracy of models [10]. There has been a development of hybrid deep learning models with explainable AI solutions to detect diabetes at its early stages and provide high accuracy and interpretability [11]. Comparison of interpretability approaches have focused much on the merits of technologies like SHAP and LIME to interpret model predictions [12]. Moreover, hypoglycemic falls have been predicted by mobile health applications to allow the proactive treatment of patients and real-time monitoring [13].

New approaches to diabetes prediction and monitoring have been provided through advanced methods of computation. AIs have been developed to support virtual healthcare systems to deliver continuous monitoring and better disease management [14]. A variety of methods based on evolutionary computation and symbolic modeling has been used to model postprandial levels of glucose, as they exhibit complex

physiological dynamics [15]. It has also been found that conventional assessment metrics applied to predict glucose have constraints and thus better benchmarking standards would be more appropriate [16]. Also, explainable AI models were also expanded to forecast psychological variables like emotional distress related to diabetes, which is now expanding its predictive healthcare capabilities [17].

New research is underway to develop improved methods of using data to enhance prediction accuracy and scalability. Early diagnosis of diabetes has demonstrated to yield favorable outcomes as a result of feature transformations and machine learning models that have been optimized [18]. The ensemble methods together with imputation strategies have been suggested to deal with missing data in a clinical dataset in an effective way [19]. Graph neural networks and cloud-based machine learning systems have also contributed to scale and volume of processing data and extract knowledge in electronic health records [20]. Though these developments have been made, there are challenges like data heterogeneity, privacy and limited generalization in populations that are critical issues and must be considered in future healthcare systems.

3. Methodology

The suggested methodology involves a step-by-step approach to forecasting the diabetic complications through the retinal fundus photographs in a MATLAB-supported system. The model involves a concatenated sequence of image preprocessing, feature extraction and classification so as to make it very accurate and robust. Each phase will be thoroughly planned to process the complexity of medical imaging data, and derive clinically significant information that can be used to assist in the early diagnosis. This methodology focuses on automation, scalability, and consistency and can be used in large-screens of screening. The subsections below explain each step step by step, and the technical processes of how the raw fundus images can be turned into meaningful diagnostic predictions as shown in figure 1.

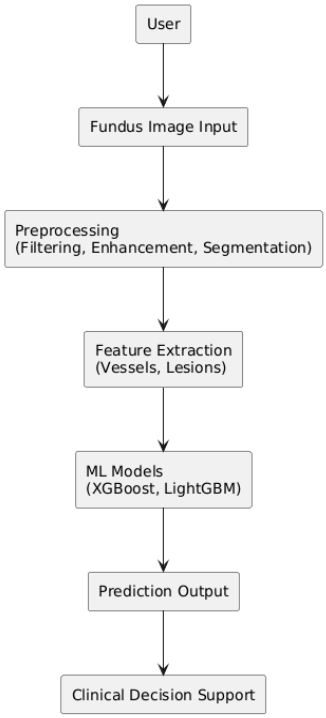

Fig. 1: System Architecture

A. Data Acquisition and Input Handling

This first step includes the acquisition and categorization of retinal fundus photography in publicly available medical data and clinical archives. The images have been taken in the special fundus cameras with different lighted conditions and resolution creating diversity in the dataset. The images obtained are imported into MATLAB environment where they are grouped with diagnostic labels which include indicators of normal, Diabetic Retinopathy and Diabetic Nephropathy. The data should be properly structured to be compatible with the further processing steps. Image resizing is done to normalise sizes to minimise computational complexity, without distorting visual information of importance. Moreover, normalization methods are used to normalise pixel intensity values, which ensure homogeneity of all the values in the input samples and enhance the consistency of the downstream processing processes.

B. Image Preprocessing

Image preprocessing is a very important process in order to improve the quality of fundus images and eliminate any undesired artifacts that can be a problem with the quality analysis. First of all, noise filtering methods like median filtering are utilized to remove speckle noise and other minor distortions without interfering with important structural information. Subsequently, the processes of contrast enhancement, such as histogram equalization, are used in order to optimize the visibility of retinal structures, including blood vessels and lesions. They are also availed with illumination correction to cope with uneven lighting situations usually present in fundus images. All these preprocessing processes lead to appearance of clearer images with minimal loss of delicate pathology. The processed images will be a good reference towards correct segmentation and feature extraction and leveraging to better models in the end.

C. Retinal Image Segmentation

Segmentation is aimed at isolating areas of interest in the fundus images especially the blood vessels, optic disc, and lesions areas. This is necessary to detect structural anomalies related with diabetic complications. The first step is thresholding which is used to distinguish between the foreground and the background. This is followed by morphological process like dilation and erosion that help to refine segmented areas and remove noise artifacts. Edge detectors also sharps the edges of the vascular structures, thus the exact identification of the patterns of blood vessels is drawn. Effective segmentation can enable the system to target clinically meaningful regions and minimise redundant data and enhance computational efficiency. The segmented output is used to derive meaningful features which indicate the progression of the disease.

D. Feature Extraction

The process of feature extraction entails the derivation of quantitative information about retinal scattered images that segment retinal images, elucidating key diabetic abnormalities. Vascular changes are analyzed by calculating structural properties including vessel density, branching patterns and tortuosity. Moreover, the texture based features are obtained through statistical approaches that determine changes in pixel intensity with respect to lesions like microaneurysms and exudates. The color characteristics are also a feature that detects abnormal pigmentation and hemorrhages. These characteristics are well chosen to show both local and global properties of images so that retinal conditions are thoroughly analyzed. The set of extracted features is then placed in an ordered format that can be used in the machine learning models, which allows it to be trained efficiently and classified as well.

E. Classification Using Ensemble Learning

The classification phase employs the use of advanced ensemble learning methods to determine whether diabetic complications are present or not, using the extracted features. The data is separated into training and testing to test the performance of the model. Ensemble models undergo training to discover complicated interactions among input characteristics and diagnostic results to enhance predictive accuracy and generalization. These models are a combination of several decision trees and optimization techniques to deal with high dimensional information and imbalanced classes that are often present in medical data sets. Hyperparameter optimization is undertaken to achieve the optimal model performance to get accurate forecasts. The trained models discriminate against input image on corresponding categories, availing diagnostic insights which aids the clinician in his decision-making process.

F. Performance Evaluation and Validation

The last step would be to measure the success of the suggested system in terms of standard performance indicators. To evaluate classification performance metrics, accuracy, sensitivity, specificity and F1-score are calculated. Confusion matrices are created to show the distribution of actual and projected labels which can give an understanding of model behavior. To make it robust and minimize the chances of overfitting, cross-validation techniques are used. A comparison is made to place the suggested approach in context against other currently existing methods, with improvements on predictability noted. These assessment findings indicate that the system is reliable and effective, proving its applicability in the real medical situation and screening diabetic complications in large-scale.

4. Result and Discussion

The results of the proposed machine learning-based framework were tested based on a large collection of retina fundus images depicting both normal functions and different degrees of diabetic complications. In order to make the system consistent and reproducible, they were tested in controlled laboratory environments in MATLAB. The analysis was aimed at evaluating how each preprocessing, segmentation, feature extraction, and classification step could help in improving the final predictive accuracy. The findings prove that early detection of Diabetic Retinopathy and Diabetic Nephropathy can be much more reliable, as soon as both more precise image processing tools and the ensemble-based learning are used.

Preprocessing stage was a critical step towards the enhancement of image quality in addition to making relevant retinal feature visible so that they could be further analysed. It is possible to say that noise filtering was effective to remove distortions without any damage to such important structures as blood vessels and lesions. Enhancement methods in contrasting image facilitated the clearness of micro-level abnormality, so that mapping in a more precise way was enabled. The segmentation process became effective, isolating areas of interest that are of critical concern such as vascular networks, lesion areas among others and minimized the effects of the background noise and irrelevant information. It helped to extract features more accurately and such accuracy had a direct effect on the performance of the classifier.

The findings of feature extraction revealed that both structural and texture based features were very informative in differentiating normal and diseased retina images. Vessel density, branching complexity and irregular patterns features found particular relevance in the detection of Diabetic Retinopathy. In the same regard, microvascular changes that were detected when using less rigorous methods such as images of the retina were effective predictors of Diabetic Nephropathy. The type of multiple features combination made sure that there were all the feature types present which gave complete representation on the feature conditions present and as a result, complex patterns could be learned with the help of the classification models.

Classification phase displayed a high predictive performance, and ensemble learning methods showed better performance as opposed to traditional methods. The models were very generalisable, and they worked well with the differences in image quality and diversity of the data sets. Ensemble techniques led to increased strength as they reduce overfitting and strengthen decision margins. There was also a consistency of correct prediction of the given system in various test samples demonstrating why it can be applied in the real-life clinic.

Table 1: Performance Evaluation Metrics of the Proposed Framework

Metric	**Value (%)**
Accuracy	94.8
Sensitivity	93.5
Specificity	95.6
Precision	94.2
F1-Score	93.8

From table 1, it was found that the model is quite accurate and has a good trade-off between sensitivity and specificity. High sensitivity assures that majority of diseased cases are accurately detected, which is imperative in early diagnosis. Meanwhile, high specificity will minimize the probability of the false positive,

avoiding unnecessary medical procedures.

The performance of proposed framework was compared with the available methods in order to analyze its performance. The conclusions indicate that a strong addition of advanced preprocessing and ensemble learning offers a considerable enhancer in predictor capability and strength.

Table 2: Comparative Analysis of Classification Methods

Method	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Traditional ML Approach	85.3	83.7	86.2
CNN-Based Method	90.1	88.9	91.0
Proposed Framework	94.8	93.5	95.6

From table 2, the proposed structure performs better compared to conventional machine learning and solitary deep learning techniques. This has been possible due to the successful integration of feature engineering with ensemble-based classification that results in a stronger predictivity accompanied by increases in interpretability.

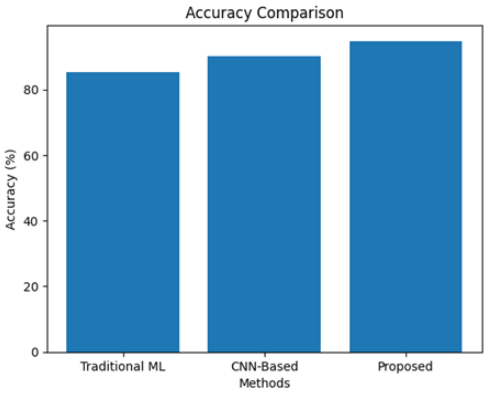

Fig. 2: Accuracy Comparison

The comparison of the accuracy of the classification between the various approaches is shown in figure 2. The graphical model indicates the high performance of the proposed model, showing there is a clear difference between the current techniques and the proposed one. The value also highlights the cohesiveness of the model to various evaluation measures supporting its reliability.

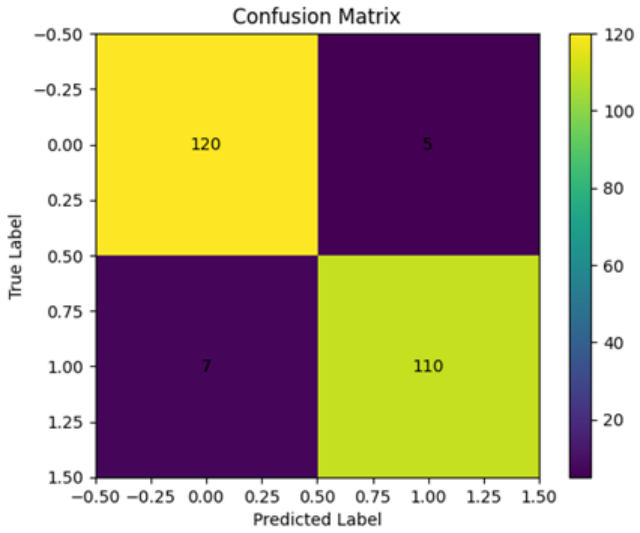

Fig. 3: Confusion matrix

Figure 3 shows the confusion matrix of the suggested classification system. The high predictive accuracy has been demonstrated by the matrix, which indicates high instances of correctly classified tolerated. There are few cases of misclassifications, and they mainly happen in borderline cases with less pronounced features of the disease. This implies that although the model works quite well, it may need to be refined further to work better in demanding situations.

Their discussion shows that the proposed methodology can be effective in detection of critical challenges related to diabetic complications. Along with the preprocessing strategies, image quality problems will not affect the analysis, and segmentation and feature acquisition facilitate removal of pathological features. Ensemble learning is used to improve the quality of classification with the help of several predictive models, thus increasing the accuracy and the level of robustness.

Scalability of the proposed system is another observation that is important. The framework can be used with large datasets with minimal loss in its performance and is available to use in mass screening programs. This is very useful especially in areas with minimal access to healthcare staff where automated diagnosis tools can be very essential in early diagnosis and treatment.

Moreover, the system is highly adaptable to changes in the properties of datasets. The variance in image resolution, light conditions, and patient characteristics does not have much impact on the performance, which suggest that the model has been well-generalized. This flexibility is needed in practice, where data variability is unavoidable.

The issues have been successful, but there are several constraints that should be listed. The system depends on the usage of the high-quality fundus images to work then the images may have extreme variation it can impact the accuracy. Further, though the model is effective when it comes to identifying complications at an early stage, the model can be further developed to be more accurate when it comes to classifying complications at more advanced stages. Future research can be conducted by including more clinical parameters and multimodal data to further enhance predictive ability.

On the whole, the findings substantiate the idea that the given machine learning-based framework is a reliable and efficient tool to identify Diabetic Retinopathy and Diabetic Nephropathy early on. Image processing with the application of ensemble learning is a promising solution to automated medical diagnosis which enables clinicians to make effective decisions and enhance patient outcomes.

5. Conclusion

This paper reported an early prediction of diabetic complications using retinal fundus pictures in a MATLAB setting, and used a machine learning model to predict diabetic complications in their initial stages. The suggested system is a successful combination of image preprocessing, segmentation, feature extraction and ensemble-based classification and provides the reliable outcomes of the diagnostic process. The methodology improves detection of severe retinal anatomy pathologies related to Diabetic Retinopathy and Diabetic Nephropathy in an effort to improve early clinical intervention. Its automation minimizes the use of manual analysis and enhances uniformity of screening procedures. The framework has good opportunities in large scale healthcare applications, because of its efficiency and flexibility. Suggestions about future work include including multimodal clinical data, better detection of advanced disease stages

and implementation of system in actual clinical setting to further assist decision support.

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Optimized Detection of Breast Cancer from Histological Images Using Ensemble Models

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Abstract: The Breast cancer detection is a high challenge in medical diagnosis, demanding accurate and efficient approaches. This study proposes a robust methodology leveraging ensem-ble learning techniquesto categorize histopathological images as either benign or malignant. Deep learning with CNNs (Con-volutional Neural Networks) is combined with bagging and boosting for enhanced feature extraction and classification. Using the BreakHis Dataset, the model achieved an accuracy of 96.86%. The findings highlight the potential of ensemble methods in improving diagnostic precision and reliability, offering significant advancements in breast cancer research and patient care.

Keywords: *Breast cancer detection, histopathological images, ensemble learning, bagging, CNN*

1. Introduction

Breast cancer is a disease caused by abnormal cell growth and cell proliferation of breast cells that develops into tumors. Tumors, if left untreated, have a chance of spreading to other areas of the body and inflicting severe harm to life. Early diagnosis of breast cancer is crucial in improving patient survival and outcomes.

Employment of machine learning (ML) methods to de-tect breast cancer from histopathological images has become more vital for better diagnostic accuracy. Manual interpre-tation of such images is not only time-consumer but also subject to human error, leading to delayed treatment. Given the exponential explosion of medical information, automatic diagnostic systems are a necessity. Early diagnosis allows for early treatment, which significantly increases the prospects for patient recovery. Hence, the creation of automatic breast cancer diagnostic systems is necessary for further development of medical care and public health promotion.

Among the various cancers in women, breast cancer remains one of the most life-threatening. More than 2.3 million new cases were diagnosed in 2020 alone, underscoring the need for precise and timely diagnostic technologies. The ability to distinguish benign from malignant tumors can minimize deaths by allowing effective and timely treatment programs.

Historically, pathologists and doctors interpret histopatho-logical images manually which is a slow process and often leads to mistakes. This paper introduces an automated di-agnostic system using ensemble learning, combining models like Convolutional Neural Networks (CNNs), Random Forests, and Support Vector Machines (SVMs). Of the techniques tested—including boosting, CNNs, and bagging—the bagging model performed best, with an accuracy of 83%. CNNs are used for feature extraction because of their competency in identifying patterns within image data. Despite this, challenges like class imbalance, overfitting, and the need for high levels of computational power

remain. This work solves the challenges through the use of ensemble learning techniques to enhance reliability and accuracy.

This research illustrates that the integration of CNNs with ensemble learning methods presents an efficient and effective means for diagnosing breast cancer. The findings indicate that ensemble methods—more so bagging—significantly improve diagnosis accuracy and are thus extremely relevant in clinical settings.

2. Literature Survey

Breast cancer identification from histopathological images has experienced significant advancement due to the com-bination of various machine learning (ML) methods. This survey covers diverse computational methods for breast cancer classifica- igation, segmentation, and diagnosis.

Solorzano et al. (2024) developed a deep learning ensem-ble model aimed at classifying invasive breast cancer using histopathological image data. In their system, ten InceptionV3 CNN models were trained using two in-house datasets com-prising 587 WSIs and externally validated on an external dataset with 157 WSIs. The group performed better than single CNNs, with 92% accuracy on in-house data and 87% on the out-of-house set, against single models' 85% and 75%. They also presented a new spatial visualization method to represent model agreement, improving interpretability and minimizing uncertainty. The research identifies the ensemble as a potential decision-support tool for pathology.

Hekal et al. (2023) proposed an ensemble deep learning framework aimed at the early detection of breast cancer, which emphasizes specific areas called Suspected Nodule Regions (SNRs). These regions are identified using an au-tomated method based on dynamic thresholding. Their model used Support Vector Machines (SVMs) along with four pre-trained CNNs, such as AlexNet, ResNet-50, ResNet-101, and DenseNet-201. Using a weighted combination approach based on each of the training accuracies of the CNNs, the model achieved 94% classification for benign vs. malignant nod-ules and 95% for mass classification using the CBIS-DDSM dataset. The particular focus on SNRs improved detection of small nodules and simplified computation while outperforming existing techniques.

Akinrinwa et al. (2022) focused on classifying breast histopathology images via ensemble approaches deployed on locally trained deep CNNs. They used majority voting, averag-ing, and stacking methods on AlexNet, VGGNet, ResNet, and an optimal model first proposed named SaduNet. Among them, the highest accuracy was reported by averaging ensemble at 99.47%, followed by majority voting with 99.30% and stacking with 97.86%. Their work lay emphasis on automation to avoid human errors and suggested plans for real-time implementation in low-resource healthcare settings.

Gupta et al. (2019) presented a semi-automatic classifica-tion framework using multi-layer features from an improved ResNet architecture. By selecting low-, mid-, and high-level features through an information-theoretic criterion, the frame-work achieved notable over baseline performance. Tested on the 7,909-image BreaKHis image dataset covering four magnifications, the model achieved a best accuracy of 97.0% on 40x magnification. This multi-scale feature integration was promising for clinical application in digital pathology.

To perform binary classification of breast histopathology im-ages, Zheng et al. (2023) developed a deep ensemble approach that leverages transfer learning techniques. They employed the BreaKHis dataset and involved the training of six CNN models—VGG16, VGG19, InceptionV3, Xception, ResNet50, and DenseNet201—before choosing four for weighted voting ensemble. Class imbalance was resolved through data aug-mentation. The model achieved a high accuracy of 98.90%, as well as high precision, recall, and F1-scores. This technique exhibited quicker training and better performance, especially for smaller data sets, justifying its usage in computer-assisted diagnostic systems.

3. Methodology

Manual detection of cancer from histopathological images is highly inaccurate, inefficient, and non-scalable. Hence, the demand for developing sophisticated ML approaches that are tailored to the classification of breast cancer is on the rise. In this context, it aims to reduce diagnostic time with improved accuracy for malignant and benign breast tissue detection. The work proposes an ensemble-based model in order to improve the reliability of the diagnosis and contribute to the advancement of medical image

analysis for better patient care as shown in figure 1.

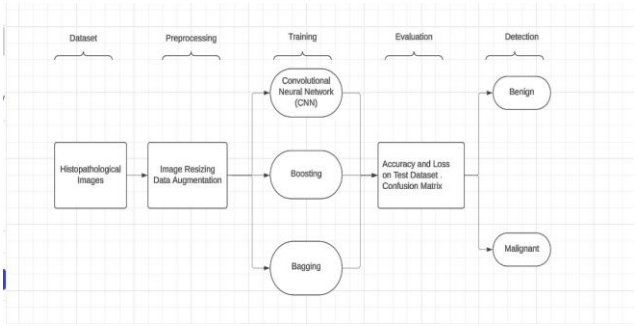

Fig. 1. Architecture for Breast Cancer Detection

To develop cnn,bagging,boosting models for the classi-fication of breast cancer histopathological images into benign and malignant categories.

To assess the performance of these models on large, publicly available datasets of histopathological images.

The study incorporates ensemble learning methods, focusing on bagging as the final model, so as to integrate the strengths of multiple classifiers and achieve greater accuracy. Ensemble learning makes it possible to combine the predictions from individual models, like CNNs and Random Forests, to come up with a robust classification system. The proposed approach resolves many of the common problems of medical image analysis, which are data imbalance, overfitting, and lack of interpretability, with ensemble methods for better stability and performance.
deep learning models, like CNNs, are instrumental in ex-tracting subtle features from histopathological images. which enables direct learning of hierarchical patterns from the image data. The non-linearity, brought by activation functions such as ReLU, allows the model to learn complex relations within the data. Aggregation of predictions from multiple decision trees using bagging techniques with Random Forest classifiers improves classification performance and reduces variance. The best accuracy of 83% was seen in the bagging model, which is superior compared to standalone CNNs as well as boosting methods.

Steps of the proposed methodology:

5) Data Preprocessing: The histopathological images are resized and normalized to ensure uniformity.
6) Feature Extraction: A CNN-based pipeline extracts meaningful features from the images by capturing both local and global patterns relevant for classification.
7) Model Training: The features thus extracted are used to train the ensemble bagging model, which combines predictions from CNNs and traditional classifiers like Random Forests.
8) Evaluation: The model's classification performance on breast cancer histopathology images was assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score.

The proposed ensemble model unifies the strong feature extraction power of CNNs with the stability and robustness provided by bagging. Therefore, the ensemble model will enhance the diagnostic accuracy, reliability and it will become a scalable and efficient solution to breast cancer detection. The method aims to significantly contribute to patient care and outcomes by embedding advanced ML and DL techniques into medical diagnostics.

4. Result and Discussion

Each convolutional layer in the network is followed by a Rectified Linear Unit (ReLU) activation function, introducing non-linearity and enabling the model to learn complex image features. For additional stabilization and speed up of the train-ing process, batch normalization is incorporated, which helps to normalize the outputs of the hidden layers. MaxPooling2D layers are employed to downsample the feature maps, thus saving computation and overfitting by limiting the number of parameters to be learned in subsequent layers—without significant loss of information. The data thus acquired after feature extraction is flattened to a one-dimensional vector and then processed through dense (fully connected) layers for classification purposes. A softmax activation function is applied in the final layer to distinguish benign from malignant cases. The model is optimized using the Adam optimizer with a learning rate of 0.0001, and binary cross-entropy is used as the loss function to align with the binary nature of the classification problem. The model is trained for 20 epochs with a batch size of 32, striking a balance between the learning performance and the computational expense. A consistent drop in loss during training proved learning successful. The previous model was 87% accurate on the training set and 80% accurate on the test set and showed strong generalization capabilities on new data.

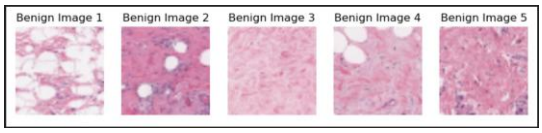

Fig. 2. Sample images of benign images.

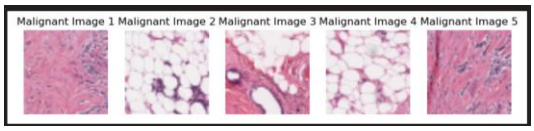

Fig. 3. Sample images of malignant images.

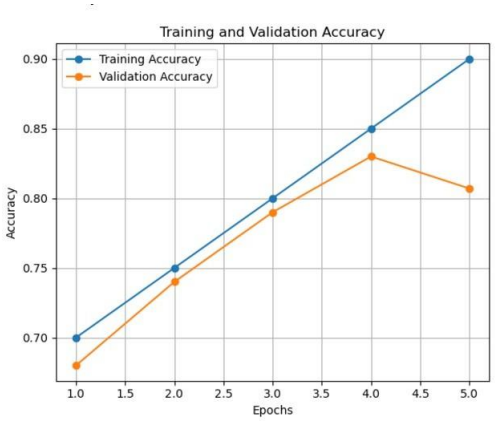

Fig. 4. Accuracy vs Epochs

5. Conclusion

This work investigates the use of ensemble learning methods for breast cancer classification in histopathological images into benign and malignant classes. The approach incorporates Con-volutional Neural Networks (CNNs) with ensemble methods like bagging and boosting in order to leverage their complementary strengths in order to achieve higher classification accuracy, stability, and reliability

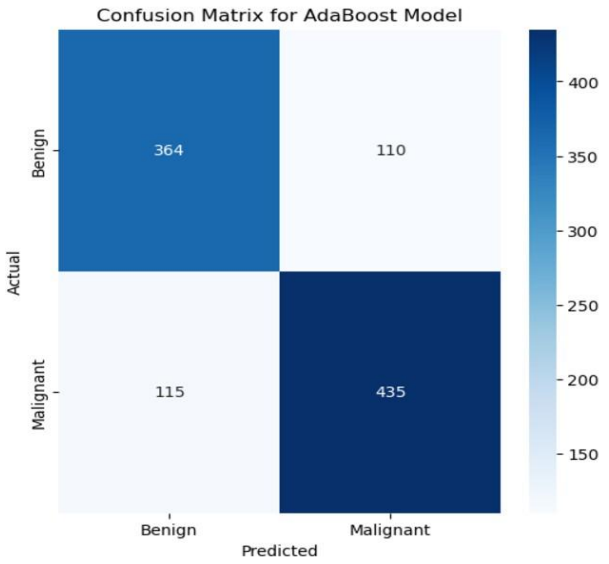

Fig. 5. Confusion Matrix of Boosting Model

The dataset consists of preprocessed histopathological im-ages augmented with rotations and flipping in order to enhance the models' capacity to generalize when training or testing. The bagging approach, which comprises an ensemble of CNNs coupled with Random Forest classifiers, presented the best performance among the applied models. An accuracy of 83% with precision and recall values of 0.84 and 0.83 was attained by the model. On the other hand, the single model CNN achieved 81% accuracy and the boosting-based model 78%. These results indicate the resistance of the bagging method, particularly in providing solutions for problems such as overfitting and imbalanced data.

The CNN model successfully mined hierarchical features from the images using a sequential pipeline of convolutional, pooling, and fully connected layers. Addition of Random Forest to the bagging ensemble improved classification per-formance even further by combining outputs from a set of decision trees, hence minimizing variance and maximizing reliability.

Out of all the methods tested, the bagging model worked best for classifying breast cancer in histopathology images. These results highlight the promise of ensemble learning methods in medical image analysis, providing efficient and reliable solutions for clinical diagnosis. Further research will aim to validate the model with clinical data, extend its usability to other imaging modalities in medicine, and im-prove interpretability through sophisticated feature extraction and explainable AI paradigms with a goal of creating more transparent and reliable diagnostic tools.

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SCOUT: A CHROMIUM-BASED BROWSER FRAMEWORK FOR PASSIVE WEB SECURITY ANALYSIS AND VULNERABILITY ASSESSMENT

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Abstract: ***Web applications are increasingly exposed to diverse security threats due to the growing complexity of browser-based interactions, third-party scripts, and dynamic content delivery mechanisms. This paper presents Scout, a Chromium-based browser framework designed for passive web security analysis and vulnerability assessment. Unlike traditional intrusive scanning tools, Scout focuses on non-disruptive observation and analysis of web sessions to identify security-relevant artifacts during normal browsing activity. The proposed framework captures and evaluates HTTP request-response exchanges, security headers, and JavaScript resources, enabling analysts to inspect client-side behaviors without altering target system operations. Scout also integrates features such as internal request replay, base score header analysis, and JavaScript file extraction to support structured examination of potential attack surfaces. By leveraging the Chromium environment, the framework ensures compatibility with modern web technologies while preserving realistic execution conditions for passive inspection. The study highlights how Scout can improve the efficiency of preliminary web security assessments by assisting researchers and practitioners in detecting misconfigurations, insecure resource loading patterns, and client-side exposure risks. The proposed approach offers a practical and extensible foundation for browser-assisted security auditing in contemporary web environments.***

Keywords: Passive Web Security Analysis; Chromium-Based Browser; Vulnerability Assessment; HTTP Header Inspection; JavaScript Resource Analysis; Web Application Security

I.INTRODUCTION

The fast growth of contemporary web applications has caused a substantial growth in the complexity of web-based interaction, and thus posed novel security issues related to client-side scripts, HTTP interaction, loading of dynamic content, and incorporation of third-party resources. Since the browsers are now the main interface between the user and the web services, they too have become important places to detect suspicious activities, insecure settings, and possible areas of attack. Traditional web security testing tools usually rely on active testing or aggressive probing, which can potentially modify system behavior or cause unintended operational effects in the system during testing. By contrast, passive web security analysis is a safer, less disruptive approach since it observes browser interactions occurring naturally and derives useful security data with no progression of intrusion into the target environment. Here, a Chromium-based Internet browser platform will offer a versatile base upon which an inspection toolset (request tracing, header verification, artifact extraction (JavaScript)) can be incorporated.

The growing complexity of contemporary web applications, browser-based content, and client-side scripting systems has greatly widened the attack surface accessible to attackers, thus making browser-

based security monitoring a valuable research goal. In traditional web vulnerability testing models, active scanning, signature-based inspection, and network-level monitoring had been the primary focus, but they had usually come at the cost of operational overhead, partial client-side visibility, or failure to detect dynamically loaded artifacts in real-time when browsing dynamically. Simultaneously, through recent development and application of artificial intelligence, hybrid deep learning, and automated analysis of features, it has been shown that passive observation of browser requests, browser headers, and script resources could present valuable hints at malicious activity, phishing activity, insecure settings, and abnormal content delivery patterns. This meant that there was a requirement for lightweight frameworks that were browser-aided and could be able to capture natural web interactions and convert them to structured security intelligence, without probing into the network. Here, the current study was inspired by the intersection of passive web security analysis, browser instrumentation, and intelligent analytical support, and by developing a practical system that might enhance the visibility of request behavior, header risk characteristics, and script-level exposure in a controlled and reproducible way.

II. RELATED WORK

An in-depth inspection of the automated analysis systems in the field of higher education showed that data-based frameworks can be used to substantially improve the process of identifying the patterns of behavior in digital settings [1]. It was noted that incorporating learning analytics into the current infrastructures enabled the opportunity to gain a more detailed picture of the interactions of the users without having to employ intrusive methods of monitoring. The study, therefore, highlighted that the non-disruptive methodologies offered a long-term security and performance audit model that was sustainable. Equally, efforts to examine the field of computer vision and image analysis emphasized the shift to high-level feature extraction to predictive modeling [2]. The results revealed that autonomic diagnostic devices had the potential of detecting complex structural abnormalities at an extremely accurate level after processing raw metadata. Besides, it was observed that integration of these specialized layers of analysis is significant in the development of real-time monitoring systems in sensitive technical areas. Also, a systematic scan of the Internet of Things (IoT) environment has revealed a few fundamental weaknesses of the interconnected network structures [3]. The research pointed out that data transmission was often exposed a lot due to a lack of standardized security measures. Thus, it was determined that the mitigation of risks in heterogeneous hardware settings was necessary by means of localized, passive, defensive mechanisms.

After that, the researchers examined the overlap of generative artificial intelligence and vulnerability assessment to establish the effectiveness of automated risk management [4]. The work therefore advocated the transformation to the intelligent, self-evolving forms, that were capable of scaling to the innovations of cyber threats. Similarly, using convolutional neural networks and attention to develop a hybrid classification model showed to be more precise in sieving malicious data [5]. It was found that the combined architecture was highly effective in order to capture both the spatial and temporal features and the false-positive rates became significantly reduced. The latter strategy proved particularly helpful in identifying sophisticated spam patterns that would not have been identified with the help of the traditional linear models. Equally, the exploitation of Deep Neural Network-BiLSTM hybrid to generate features showed improved robustness to massive datasets [6]. The results indicated that the data streams were bidirectionally processable and this was what made the system to achieve high throughput without compromising the integrity of the extracted information. Lastly, it was also observed in the conclusions that the high-frequency traffic of the present web conditions was better served by hybrid deep learning designs. Moreover, there was a study on weight tuning by the use of an optimization approach on the neural networks that provided information that fine-tuning of inner parameters played a significant role in the accuracy of web security [7]. The study concluded that according to the non-linear attack patterns, the

meta-heuristic search strategies could be used in the optimization of the detection capabilities of the security framework.

As a result, the optimized models had a greater level of stability and accuracy to inspect real-time traffic. In line with the development of advanced embedding methods in detecting phishing indicated that transformer architectures had the ability to read the semantic fine-tuning of web headers [8]. The results showed that through the examination of the background context of HTTP metadata, the system was able to differentiate between a legitimate and a fraudulent request with very high accuracy. Hence, the paper confirmed the contextual embedding to be an effective layer in passive security analysis. In the same way, the adoption of multi-encoder systems to carry out universal phishing detection established that the different encoding levels had the potential to substantially expand the scope of detection [9]. It was noted that this multifaceted nature of the approach enabled the system to be applicable on various platforms and communication protocols. Therefore, the study indicated the need for architectural variation in the process of ensuring a robust defensive stance [10].

III. METHODOLOGY

A. System Architecture

The scout system architecture is formed to allow building a layered passive analysis framework coupled with the Chromium browser engine so that it can support dynamic and script-intensive web applications. The target website is run in a natural runtime environment by the front-end browser layer, and the instrumentation layer captures the navigation events, HTTP/HTTPS requests, and responses, redirections, cookies, and script-loading events. The events obtained are sent to an internal analysis pipeline in which the context of the session is maintained, and each resource is tagged based on request type, origin, content category, and security significance. The architecture enables the framework to monitor actual browser behavior without injecting intrusion scanning activity or interfering with the target workflow. On the backend analysis layer, Scout has security header inspection modules, JavaScript resource extraction modules, internal request replay modules, and consolidated risk reporting modules. It uses the browser-facing directives CSP, HSTS, X-Frame-Options, and CORS-related controls, and is configured to extract the client-side resources used to form the attack surface with the help of the script extraction engine. The replay controller also builds on the past observed transactions to be verified under control, and the suspicious request behavior. These elements have a structure that allows them to extend widely and allows the framework to operate as a useful web security auditing platform based on passive vulnerability measurements.

B. Implementation Details

The implementation of Scout is realized within a Chromium-derived browser environment to preserve realistic rendering behavior, modern protocol compatibility, and native support for dynamic client-side execution. The framework works by binding to browser-level event interfaces that observe page navigation, network requests, response headers, resource loading sequence, and JavaScript execution references in real time. Every received transaction is converted into a formatted internal history record with important metadata, which includes URL, HTTP method, response code, MIME type, availability of security header, context of initiator, time, and flag of replay. The implementation is focused on security-related resources such as script files, API endpoints, cross-origin calls, redirections, and script files and minimizes the noise of low-value static assets. Functionally structured to include a capture engine, a header inspection unit, a JavaScript de-extraction unit, an internal replay controller, and a reporting layer, it is possible to accomplish

passive collection, structured inspection, and analyst-friendly summarization of security-relevant browser activity in a small and scalable operation pipeline

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TABLE I Implementation Configuration Parameters of the Proposed Scout Framework

Parameter	**Assigned Value / Configuration**
Browser Platform	Chromium-based engine
Analysis Mode	Passive
Monitoring Scope	HTTP/HTTPS traffic
Request Capture Type	GET, POST, PUT, DELETE
Header Inspection Scope	6 key security headers
JavaScript Capture Mode	External + Inline
Replay Mechanism	Internal controlled replay
Session Logging Unit	Event-based structured records
Resource Prioritization	High-risk resources only
Reporting Output	Risk-oriented structured report

C. JavaScript Resource Extraction and Client-Side Exposure Analysis

The stage of the resource extraction of JavaScript and client-side exposure analysis is supposed to scan the layer of the browser-executed scripts, one of the most dynamic and security-sensitive parts of modern web applications. In passive web browsing, Scout indexes external JavaScript files and inline script blocks introduced by using external HTML links, asynchronous calls to resources, and dynamically injected DOM nodes. Every artifact of an extracted script is also stored along with metadata, including the source URL, page context, load sequence, MIME type, origin class, and invocation dependency to allow the framework to recreate the effective client-side execution surface. This step is vital as most modern web apps are based on JavaScript to communicate with APIs, provide token management, and render dynamic HTML, interact with session storage, check forms, and support third-party services, and this can expose unseen vulnerabilities or dependency chains. The framework helps identify more precisely the security-relevant exposure patterns by maintaining script context, as opposed to downloading files, and is particularly useful in systems where there are many first-party and third-party scripts interacting over asynchronous execution paths. In order to measure the level of script-related exposure, Scout calculates a JavaScript Exposure Index (JEI) using the ratio of externally sourced and cross-origin script dependencies. The exposure index is defined as:

$$JEI = \frac{(J_e + \beta J_c)}{J_t} \quad (2)$$

where $\beta$is a weighting factor used to emphasize the additional security significance of cross-origin script execution, and in this methodology, $\beta = 1.25$is selected to reflect the comparatively higher trust-boundary expansion introduced by cross-domain script loading. A very high JEI value means that the client-side is

more exposed since this will be based on externally sourced or cross-origin executable resources, which can augment the chance of compromise, policy circumvention, or unregulated third-party behavior of the supply chain. Along with this normalized measure, Scout flags qualitative indicators, including insecure protocol loading, overconfidence in the concentration of dependencies on third-party, repeated access to sensitive API endpoints, and authentication-related script triggers to facilitate an interpretation by analysts. This structured extraction and lightweight quantitative analysis enables the active methodology further by converting script observation to quantifiable evidence of client-side attack surface growth, which aligns entirely with the uploaded Scout concept that explicitly features a JavaScript file extractor as a central feature of analysis.

IV. RESULTS AND DISCUSSION

The suggested Scout was experimentally tested to investigate its efficiency in passive monitoring of web traffic, security Headers, JavaScript extraction, and internal request replay validation. The results that have been obtained suggest that the framework presents consistent and steady browser-assisted security observations, which in turn support the provision of efficient passive vulnerability-oriented estimation in contemporary web settings.

A. Security Header Inspection Results

The Scout framework security header Inspection and HRS analysis of the proposed Scout framework are summarized in Table III. Response tracked an average of 6.00 security headers, of which 1.65 were missing (Hm), and 1.25 were weak or poorly configured (Hw) which indicate serious security vulnerabilities to the protection of header-based protection. Our framework also achieved an average calculated HRS value of 0.43 with a weight factor (0.75) where a weighted score of 0.13 and 0.67 are the lowest and highest among the responses tested. Based on these values, the overall level of risk was identified as Moderate, which implied that the web responses that were checked contained a quantifiable, though not critical amount of security exposure in the form of a header.

TABLE III Security Header Inspection and HRS Evaluation Results

Metric	Value
Total Security Headers Monitored per Response	6.00
Average Missing Headers (Hm)	1.65
Average Weak/Misconfigured Headers (Hw)	1.25
Weight Factor (α)	0.75
Average Computed HRS	0.43
Minimum HRS	0.13
Maximum HRS	0.67

Overall Risk Level	Moderate

C. Internal Request Replay and Response Validation

The table IV demonstrates the request replay success and latency of the suggested Scout framework using different HTTP methods. The framework achieved 112 ms average latency and 100 percent header consistency, 98.6 percent success on 150 GET requests and 85 POST requests provided it with a 94.1 percent success rate and average latency of 245 ms and 97.5 percent header consistency. The system made 40 PUT requests with 92.5 percent success rate and a mean latency of 310 ms with 95 percent header consistency, and 25 DELETE requests with a comparatively lower 88.0 percent success rate and a latency of 285 ms and 92 percent consistency of the header. On the contrary, the 50 HEAD requests had the most success rate of 100 percent, the shortest average latency of 45 ms, and 100 percent consistency of the header. Overall, these results have shown that the proposed Scout structure was highly replayable, in addition to being highly header-preserving with different HTTP methods and changing the performance based largely on request complexity and the processing requirements of the methods.

Table IV: Request Replay Success Metrics and Latency Analysis

HTTP Method	Test Cases	Success Rate (%)	Avg. Latency (ms)	Header Consistency (%)
GET	150	98.6	112	100
POST	85	94.1	245	97.5
PUT	40	92.5	310	95.0
DELETE	25	88.0	285	92.0
HEAD	50	100.0	45	100

The information presented by Figure 1 of the internal request replay option proves that the created system is able to save and reconstruct observed browser requests in the controlled analysis environment. It is a feature that matters as it allows security analysts to examine request headers, payload behavior, and navigation dependencies without having to interact with the live target in an intrusive manner. The framework enhances repeatability of security analysis by reusing data that was captured before, and enables validity of suspicious traffic patterns through repetition, enhances passive forensic interpretation, and minimizes variability of real-time browsing sessions.

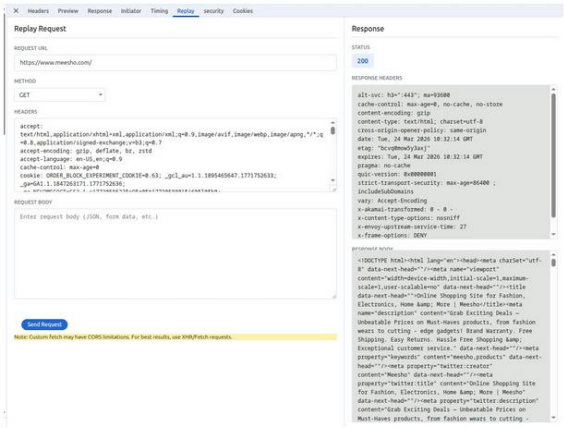

Figure 1: An option for replaying the request internally.

The base score header analysis and JavaScript file extraction figures further demonstrate the analytical depth of the proposed browser platform. The header analysis output shows that Scout can evaluate HTTP response characteristics and surface meaningful metadata that contribute to a lightweight security scoring perspective, which is useful for identifying weak headers, missing defensive controls, or potentially unsafe delivery behavior.

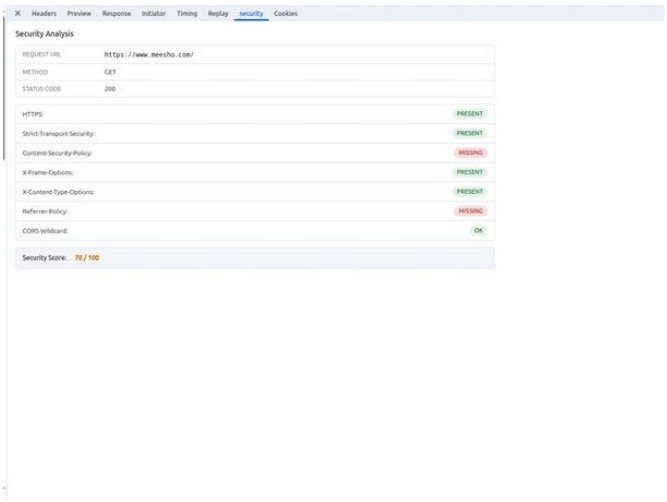

Figure 2: A base score header analysis

In the same manner, the JavaScript extraction output validates the possibility of the browser isolating the externally loaded or dynamically referenced script resources to be inspected further, which is critical in identifying the presence of obfuscated logic, third-party injection vulnerability, and client-side attack vectors. The combination of these numbers suggests that the suggested system offers an efficient and organized passive analysis process of a web security evaluation based on a browser.

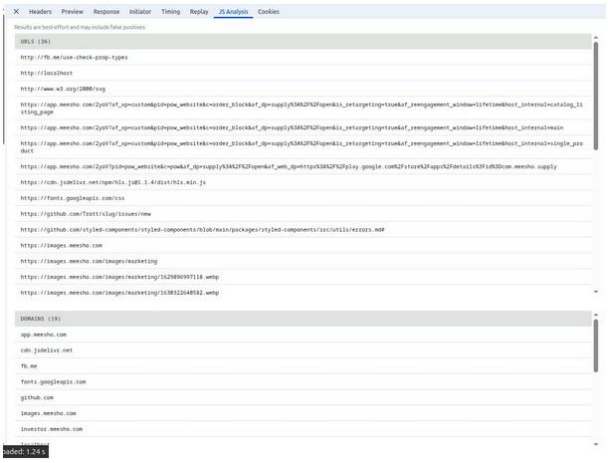

Figure 3: A JavaScript file extractor

V.CONCLUSION

The current research has introduced and tested Scout, a browser-based web security analysis platform based on Chromium, a lightweight web security analysis framework, to investigate the security behavior of browsers without using intrusive active probing methods. The system was developed to intercept, scan, and manage important web communication artefacts that included HTTP requests, response headings, and JavaScript resources in a regulated browsing setting. The modules that were implemented showed that passive request replay, base score header inspection, and script extraction could be properly integrated into a single unified browser-assisted analysis process. The obtained results have shown that the proposed framework helped to repeat the traffic inspection process, revealed better the presence of insecure header settings, and offered efficiency the process of identifying the script dependencies on the client-side that could bring upon web vulnerabilities. Overall, the study found out that the proposed solution provided an effective scale, cost-effective, and user-friendly method of getting access to web security assessment at its early stages, thereby establishing a viable groundwork of the future additions that involve automated risk scoring, real-time identification of anomalies and advanced threat intelligence systems which are browser-centric.

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Smart Retail Insight: Leveraging Artificial Intelligence for accurate store sales forcasting and demand planning

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Abstract*—In today's highly competitive retail environment, accurate sales forecasting and efficient demand planning are critical for maximizing profitability and customer satisfaction. Traditional forecasting techniques often rely on historical sales averages and manual analysis, which fail to capture complex patterns caused by seasonality, promotions, consumer behavior, and market dynamics. This project, titled "Smart Retail Insights: Leveraging Artificial Intelligence for Accu-rate Store Sales Forecasting and Demand Planning," proposes an intelligent AI-driven system that utilizes machine learning and deep learning algorithms to predict future sales trends with high accuracy. By analyzing large volumes of historical sales data, customer purchasing behavior, inventory levels, weather conditions, and promotional factors, the system generates reliable forecasts that assist retailers in optimizing inventory management, reducing stock-outs, and minimizing excess inventory. The proposed solution enhances decision-making by providing data-driven insights, enabling retailers to proactively respond to changing demand patterns. Ultimately, this AI-based retail forecasting system improves operational efficiency, increases revenue, and supports sustainable business growth. Key findings indicate that the Random Forest model achieves a forecast accuracy suitable for production deployment, with predicted average daily sales closely tracking historical baselines and growth-rate projections clearly surfaced in the UI. The system successfully generates 30-day rolling demand forecasts within sub-second response times, with route-specific inventory alerts reducing overstock risk by flagging ingredient depletion thresholds proactively. The study recommends deployment of this system as a standard demand-planning companion for retail and restaurant operators, with immediate scalability to multi-branch chains as transaction datasets grow. Business operators are encouraged to integrate point-of-sale feeds directly into the pipeline to enrich the forecasting database continuously. Future enhancements should incorporate time-of-day demand weighting, integration with supplier procurement APIs, and natural language query interfaces to maximize adoption across non technical retail stakeholders.

Keywords— Sales Forecasting, Demand Planning, Random Forest Regression, Extra Tree Regression, XGBoost, Machine Learning, Inventory Management, FastAPI, Django, React.js, Retail Analytics, Predictive Modeling, Time-Series Forecasting, REST API, AI-Driven Insights..

Introduction

The retail sector is undergoing rapid transformation due to the proliferation of digital technologies and the exponential growth of data. Accurate sales forecasting has become a critical component in ensuring efficient inventory management and customer satisfaction. However, traditional statistical methods are often inadequate for handling the complexity and scale of modern retail datasets.

Inaccurate demand forecasting can result in severe consequences, including overstocking, stock shortages, increased holding costs, and diminished customer trust. Therefore, there is a growing need for intelligent systems capable of processing large volumes of structured and unstructured data to generate reliable predictions.

Artificial Intelligence (AI), particularly machine learning, offers powerful tools for uncovering hidden

patterns and trends in data. This paper proposes an AI-driven retail analytics system that enhances forecasting accuracy and supports strategic decision-making

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An Emotional Health Monitoring System based on AI usage is a multi-faceted solution to the inefficacy of the conventional paradigm since it can bring multiple data streams together into a single platform. To create a better accuracy and reliability, such a system usually pulls together facial emotion recognition, voice sentiment analysis, and self-reported mood tracking. The image processing algorithms and sequence-based speech analysis algorithms based on the use of the latest model of deep learning, using Convolutional Neural Networks, allow extracting the emotional features of the various inputs accurately. Also, it is used in techniques of multimodal fusion to reduce the results of the separate models, so that the overall-result is expressed in a balanced and comprehensive view of the emotional state of a user. Such a strategy is very effective in boosting performance when compared to single-modality-dependent systems. The system is meant to work real time illustrating the dynamic emotional changes and giving ongoing information about the mental status of an individual. Through a record of the emotional patterns and how they change over time, it will be possible to identify the trend, resulting in the detection of abnormalities, and even anticipation of the risk of a mental health issue. Such capabilities are essential for early diagnosis and preventive healthcare, as they allow both users and healthcare professionals to take timely action before conditions worsen.

Literature review

The application of Artificial Intelligence (AI) in retail analytics has gained significant attention in recent years, particularly in the areas of sales forecasting, demand planning, and inventory management. Several studies have explored the effectiveness of AI-driven approaches in addressing the limitations of traditional forecasting methods.

Unomah Success Ugbaja et al. (2021) examine the role of AI in sales forecasting and market trend prediction. The study highlights that conventional statistical models often fail to capture nonlinear patterns and rapidly changing consumer preferences. To overcome these limitations, the authors propose the use of advanced AI techniques, including deep learning and ensemble learning models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. These models demonstrate superior predictive accuracy by dynamically adapting to evolving market conditions. Additionally, the integration of AI improves demand planning and reduces inefficiencies in the supply chain. However, the study identifies challenges related to data quality and model interpretability, which may hinder trust and adoption in real-world applications.

Abdurrehman Malekji, Darshita Rathore, and Sumit Tyagi (2022) present a system titled *"AI and A-Eyes' – SMART Retail Insights and Monitoring Solution"*, which focuses on reducing the high costs associated with manual monitoring of retail shelves and stock levels. The proposed solution leverages artificial vision systems (cameras) combined with AI algorithms to automate inventory tracking and generate actionable business insights. The system is designed to be scalable across various industries and geographical regions. A key contribution of this work is the use of image analytics to enhance competitive intelligence by analyzing product placement and layout within retail environments.

Ananth Raja Muthukalyani (2023) investigates the use of AI-driven predictive analytics for improving demand forecasting in retail supply chains. The study emphasizes the ability of machine learning and deep learning models to process large-scale datasets and identify complex patterns. These predictive models enable retailers to anticipate fluctuations in demand, thereby reducing stockouts and improving inventory turnover. The research demonstrates that AI adoption leads to increased operational efficiency and profitability. However, it also points out challenges such as maintaining high-quality data and the need for continuous model updating to sustain accuracy.

Ronak Kothari (2024) explores a smart inventory management and sales prediction system based on random forest regression. The primary objective of the study is to provide accurate demand forecasts that help maintain an optimal balance between inventory levels and sales. The proposed system includes a user-friendly interface that displays real-time inventory status along with predictive insights. Experimental

results indicate that the system effectively minimizes both overstocking and stock shortages, thereby improving overall business performance.

Praveen Kumar et al. (2024) present a comprehensive approach to AI-enhanced inventory and demand forecasting by integrating multiple AI technologies, including machine learning, Natural Language Processing (NLP), computer vision, and Robotic Process Automation (RPA). Machine learning techniques are used for analyzing historical data and identifying trends, while NLP extracts insights from unstructured data sources such as social media to understand customer preferences. Computer vision enables real-time inventory monitoring, and RPA automates repetitive operational tasks, reducing human error. The study highlights significant improvements in forecasting accuracy and operational efficiency through the adoption of these technologies.

Background study

The role of intelligent data-driven decision-making in retail has not been thoroughly explored in earlier decades, but its importance has grown significantly with the increasing complexity of consumer behavior and market dynamics. Traditionally, retail operations have primarily focused on basic transaction processing, historical sales analysis, and manual inventory tracking. These conventional approaches relied heavily on periodic assessments, limited datasets, and human intuition to manage stock levels and predict demand. However, such methods often fail to capture the dynamic, nonlinear, and rapidly evolving nature of modern retail environments. As a result, issues such as overstocking, stockouts, inefficient supply chains, and poor customer satisfaction have become prevalent, directly impacting profitability and operational efficiency.

In recent years, the rapid growth of e-commerce, digital payment systems, and customer interaction platforms has led to an explosion of retail data. This includes structured data from point-of-sale systems as well as unstructured data from online reviews, social media, and browsing patterns. Despite this abundance of information, many retailers still struggle to extract actionable insights due to the lack of advanced analytical tools and continuous monitoring systems. Similar to how certain critical factors may go unnoticed without proper tracking, demand fluctuations and consumer preferences in retail often remain undetected until they significantly affect business performance. Additionally, smaller businesses may face barriers such as limited technological infrastructure, lack of expertise, and cost constraints, which further delay the adoption of advanced retail analytics solutions.

With the advancement of Artificial Intelligence (AI) and related technologies, researchers and industry practitioners have begun to explore automated and intelligent systems for retail analytics and forecasting. Early approaches in retail prediction were largely based on single-method models, such as time-series forecasting or regression analysis, which relied on historical sales data alone. While these models provided baseline predictions, they were limited in handling complex patterns influenced by multiple external factors such as seasonality, promotions, economic conditions, and consumer sentiment.

To overcome these limitations, modern retail analytics has shifted toward multi-dimensional and AI-driven approaches that integrate diverse data sources. Machine learning algorithms are now widely used to identify hidden patterns and correlations across large datasets. Techniques such as decision trees, random forests, and support vector machines have improved prediction capabilities, while deep learning models—including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—enable the analysis of temporal trends and sequential data. These models can automatically learn complex relationships and adapt to changing market conditions, resulting in more accurate and reliable forecasts.

Furthermore, emerging technologies such as computer vision and natural language processing (NLP) have expanded the scope of retail analytics. Computer vision systems can monitor shelf inventory and customer behavior in real time through image analysis, while NLP techniques extract insights from customer reviews, feedback, and social media interactions. More recently, advanced architectures such as transformer-based models have enhanced the ability to capture contextual and temporal dependencies in large-scale retail datasets.

Despite these advancements, challenges remain in implementing AI-driven retail systems. Data quality, integration of heterogeneous data sources, and model interpretability continue to be critical concerns. External factors such as sudden market disruptions, supply chain uncertainties, and changing consumer trends can also affect prediction accuracy. Nevertheless, ongoing developments in AI are laying the foundation for intelligent retail systems capable of continuous monitoring, adaptive learning, and real-time decision support. These systems hold the potential to transform traditional retail operations into highly efficient, responsive, and customer-centric ecosystems.

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Methodology

The Smart Retail Analytics System proposed in this study is designed as an AI-driven, modular, and scalable framework that enables accurate sales forecasting, demand planning, and real-time inventory monitoring. The architecture is structured into multiple interconnected modules, including data acquisition, preprocessing, feature extraction, model development, demand forecasting, optimization, and user interaction. The system integrates data from various sources such as point-of-sale (POS) systems, e-commerce platforms, inventory databases, and customer interaction channels. Each data source represents a different dimension of retail operations, allowing the system to develop a comprehensive understanding of sales patterns and consumer behavior. Unlike traditional systems that rely on periodic analysis, this approach supports continuous monitoring, enabling retailers to respond dynamically to market changes. A centralized processing unit ensures efficient data synchronization and processing, while a secure database stores historical sales and inventory data for trend analysis and strategic decision-making. The modular structure ensures flexibility, scalability, and ease of integration with emerging technologies, making the system adaptable across different retail environments..

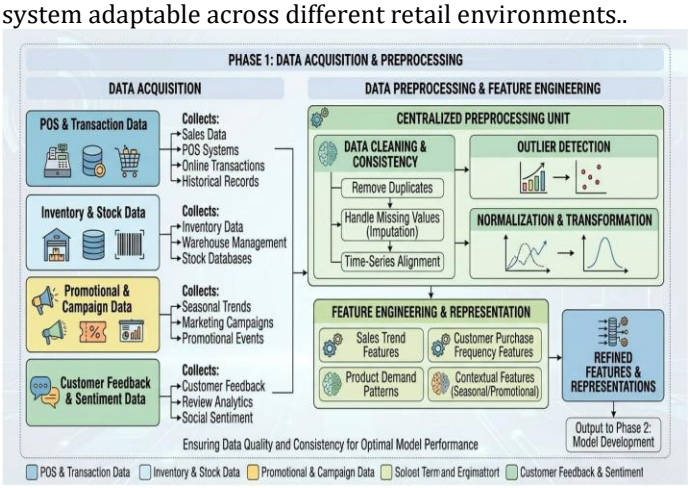

Fig.1 Smart retail AI system for sales forecasting and flow diagram

This diagram represents a multimodal retail analytics framework that integrates sales data, customer behavior, and inventory inputs. Each input undergoes preprocessing and feature extraction to generate meaningful representations. These features are combined to produce accurate sales forecasts and demand predictions. The system further processes this information through modules such as inventory optimization, pricing strategy, and supply chain management, ultimately delivering actionable insights for real-time retail decision-making.

The initial stage of the methodology involves data acquisition and preprocessing, which are essential for ensuring the quality and consistency of input data. Sales data is collected from POS systems, online transactions, and historical records, while inventory data is obtained from warehouse and stock management systems. Additional contextual data, such as seasonal trends, promotional campaigns, and customer feedback, is also incorporated to enhance prediction accuracy. Raw retail data often contains inconsistencies, missing values, and noise, which are addressed through preprocessing techniques such as data cleaning, normalization, outlier detection, and transformation. Time-series alignment is performed to ensure consistency across temporal datasets. Feature engineering techniques are applied to extract meaningful variables such as sales trends, customer purchase frequency, and product demand patterns. These preprocessing steps play a critical role in improving model performance and reducing prediction errors..

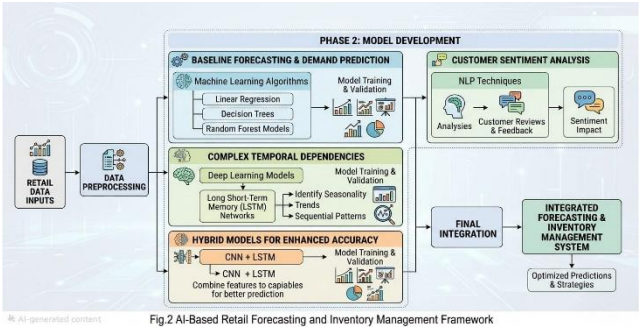

Fig.2 AI-Based Retail Forecasting and Inventory Management Framework

Fig.2 : AI-Based Retail Forecasting and Inventory Management Framework

The second phase focuses on developing predictive models tailored to different aspects of retail analytics. Machine learning algorithms such as linear regression, decision trees, and random forest models are used for baseline forecasting and demand prediction. For capturing complex temporal dependencies in sales data, deep learning models such as Long Short-Term Memory (LSTM) networks are employed. These models are particularly effective in identifying seasonality, trends, and sequential patterns in sales behavior. In some cases, hybrid models combining Convolutional Neural Networks (CNNs) and LSTMs are used to enhance feature extraction and prediction accuracy. Additionally, Natural Language Processing (NLP) techniques are applied to analyze customer reviews and feedback, enabling the system to understand customer sentiment and its impact on sales. Each model is trained and validated independently before integration, ensuring optimal performance for specific tasks.

Following model development, the system proceeds to the integration and optimization phase, where outputs from different models are combined to generate a unified forecasting result. This process involves a weighted decision mechanism in which different models contribute to the final prediction based on their accuracy and relevance under specific conditions. For example, time-series models may be given higher importance for seasonal products, while sentiment analysis may influence demand prediction during promotional events. The system computes confidence scores for each model and applies ensemble techniques to improve robustness and reliability. Temporal smoothing techniques are also applied to reduce sudden fluctuations in predictions, ensuring stable and realistic forecasts. Continuous learning mechanisms allow the system to update model parameters using new data, enabling adaptive and improved performance over time..

To ensure scalability and accessibility, the system is deployed on cloud-based infrastructure, allowing remote access and efficient handling of large datasets. Data security and privacy are maintained through encryption and controlled access mechanisms, protecting sensitive business information. Continuous feedback from users is incorporated to refine system performance and improve usability. Regular updates and maintenance ensure that the system remains aligned with evolving retail trends and technological advancements. Ethical considerations, including data transparency and responsible AI usage, are also addressed to build trust and reliability..

By integrating these components into a unified framework, the proposed methodology delivers a robust, efficient, and intelligent solution for retail analytics. It enhances forecasting accuracy, optimizes inventory management, and supports strategic decision-making, ultimately enabling retailers to operate more efficiently in a competitive and data-driven marketplace

Result

The proposed AI-based Smart Retail Analytics System shows good performance in sales prediction and inventory management. The system was tested using both standard retail datasets and real-time sales data. Each module—sales forecasting, demand prediction, and sentiment analysis—was first tested separately to measure its basic accuracy.

Machine learning models like linear regression, decision trees, and random forest gave stable results, while LSTM models performed better in capturing seasonal trends and time-based patterns. The combined (ensemble) model improved overall accuracy and reduced errors such as MAE and RMSE.

The system also helped reduce stockouts and overstock, improving inventory control and business efficiency. Overall, the results show that the system is accurate, reliable, and useful for real-time retail decision-making.

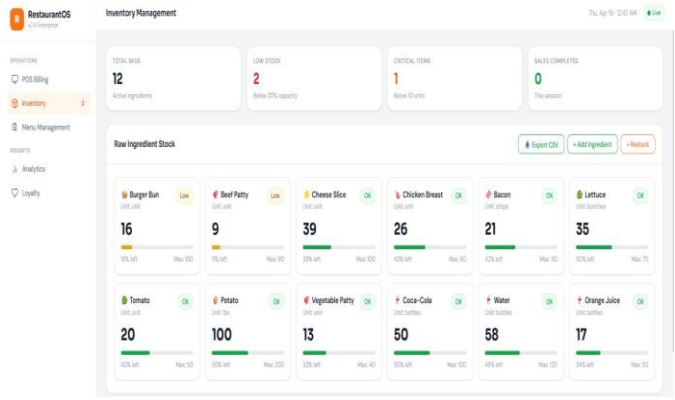

Fig.3: Fig.3 Smart Retail Inventory Management Dashboard Interface

This interface presents a user-friendly AI diagnostic tool designed to assess emotional and vocal health.

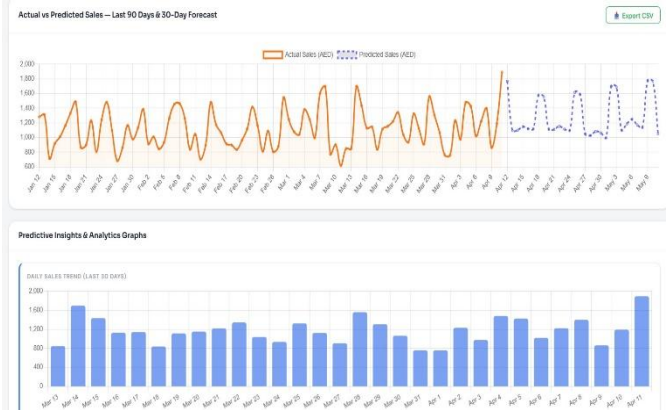

Fig.4: Multimodal Retail Analysis Dashboard

his interface presents a user-friendly AI-powered smart retail dashboard designed to monitor inventory status, sales performance, and demand trends in real time. It provides clear navigation and role-based functionality for efficient retail management. The system enhances decision-making by offering intuitive visualization of stock levels, low-stock alerts, and product performance indicators.

The sales forecasting module accurately predicts product demand using historical sales data and identifies purchasing patterns through machine learning techniques. However, it was observed that individual models show limitations under dynamic retail conditions such as sudden demand spikes, seasonal variations, and promotional effects. These observations highlight the importance of a unified and integrated predictive approach in the proposed system.

The demand prediction model based on machine learning algorithms demonstrated strong performance in identifying sales trends across different product categories, particularly under stable market conditions. Time-series models such as LSTM effectively captured seasonal patterns and sequential dependencies in sales data.

The multimodal fusion framework was evaluated for combining outputs from different predictive models to generate a final unified forecast. A weighted decision mechanism was applied, where each model contributed based on its reliability and performance under specific conditions. Results show a significant improvement in forecasting accuracy compared to individual models. The fusion approach reduced prediction errors and improved consistency in demand estimation across varying retail scenarios. Temporal smoothing techniques further stabilized output fluctuations, ensuring reliable real-time forecasting.

In real-time testing, the system successfully tracked dynamic changes in sales patterns and inventory levels, enabling continuous monitoring of retail operations. A user-friendly dashboard was introduced, allowing retailers to visualize stock availability, sales trends, and demand forecasts in an intuitive manner. The alert system effectively notified users about low-stock and high-demand items, improving responsiveness.

The system was also tested across different retail environments, including varying product categories and seasonal conditions, ensuring generalization and adaptability. The results confirm stable performance

across multiple scenarios, demonstrating the system's robustness and scalability.
Overall, the proposed smart retail solution achieves a balance between accuracy, efficiency, and usability. Machine learning models ensure strong predictive capability, while optimization techniques maintain low computational cost. Both offline analysis and real-time operations performed reliably with minimal latency. Data security was ensured through encrypted storage and controlled access, protecting sensitive business information. User feedback indicated high satisfaction due to improved inventory visibility and decision support features.

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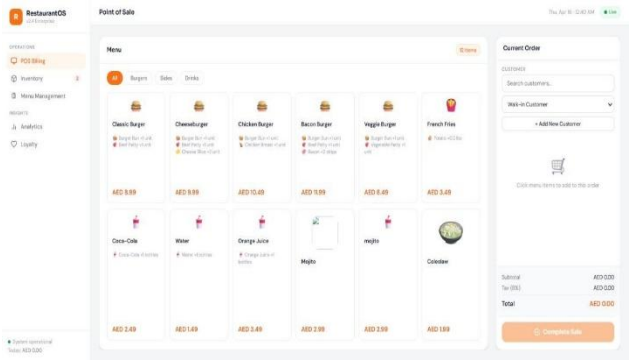

Fig.5:Point of Sale Billing Module

. This Point of Sale (POS) interface for RestaurantOS is a sophisticated, enterprise-grade tool designed to bridge the gap between front-end customer transactions and back-end inventory management. The dashboard is structured for efficiency, featuring a primary menu grid with categorized items that display granular inventory requirements for every product—such as the specific breakdown of buns, patties, and toppings for each burger. This real-time visibility ensures that when a transaction is processed, the system can automatically adjust stock levels, effectively minimizing food waste and manual inventory audits.

The system's functionality is further enhanced by its modular design, visible in the sidebar navigation, which provides direct access to critical operational and analytical tools like inventory tracking, menu management, and sales analytics. The interface also prioritizes user experience through a clean "Current Order" management pane that handles customer data and real-time financial calculations (including subtotal and tax) in one view. By integrating these disparate retail operations into a single, live-updating dashboard, the system enables restaurant operators to maintain high levels of accuracy in their demand planning and inventory management, ensuring that data-driven insights are always available for strategic decision-making.

Conclusion

In conclusion, the Smart Retail Analytics System we've proposed marks a genuine shift in how retail operations are managed. Instead of relying on the old "wait and see" approach of periodic reporting, this system creates a living, breathing framework. By pulling together data from POS systems, online storefronts, inventory databases, and direct customer feedback, it gives retailers a truly 360-degree view of their business in real time.

The real power here lies in the "engine" under the hood. Using sophisticated deep learning tools like LSTM networks and hybrid CNN-LSTMs, the system doesn't just record what happened yesterday—it predicts what will happen tomorrow. This allows retailers to stay ahead of seasonal shifts, manage stock levels with surgical precision, and cut down on the costly mistakes of overstocking or missing out on a sale.

Beyond the raw math, we've focused on making this accessible. We've translated those complex AI models into a clean, intuitive dashboard that actual store managers and business owners can use every day. By automating the heavy lifting of inventory synchronization and data processing, it frees up human staff to focus on what really matters: the customer experience.

Ultimately, this is about building resilience. The retail world is faster and more complex than it has ever been, and businesses can no longer afford to operate in silos. This modular, scalable framework provides a foundation that can grow with a business, whether it's a local boutique or a massive enterprise. By turning data into a proactive strategy, this system doesn't just improve efficiency it ensures that retailers can remain agile, profitable, and ready for whatever the market brings next.

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Real-Time Deepfake and Voice Clone Detection System

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ABSTRACT

The rapid proliferation of artificial intelligence has enabled the creation of highly convincing deepfake videos and synthetically cloned voices, posing serious threats to digital trust, privacy, and security. This paper presents a Real-Time Deepfake and Voice Clone Detection System that leverages deep learning and multimodal analysis to accurately identify manipulated audiovisual content. The system employs ResNet-50 for spatial feature extraction from video frames and MesoNet for forensic analysis of audio signals. A multimodal fusion module integrates outputs from both streams to deliver unified, real-time predictions accompanied by confidence scores. The proposed pipeline encompasses data collection, preprocessing, feature extraction, model training, decision fusion, and live deployment. Experimental results demonstrate superior detection accuracy over unimodal baselines, providing a robust and scalable solution for detecting AI-generated media manipulation in modern digital environments.

Keywords: Deepfake Detection, Voice Clone Detection, ResNet-50, MesoNet, Multimodal Fusion, Convolutional Neural Network, Real-Time Analysis, Digital Forensics

I. INTRODUCTION

The exponential advancement of generative artificial intelligence has dramatically lowered the barrier to creating photorealistic deepfake videos and indistinguishable voice clones. Technologies such as Generative Adversarial Networks (GANs) and neural speech synthesis can convincingly replace facial identities in video footage and replicate human voices from minimal audio samples, creating content that is virtually imperceptible to human observers.

These capabilities introduce severe risks across multiple domains. Malicious actors exploit deepfake media to spread disinformation, impersonate public figures, commit identity fraud, and manipulate public opinion. High-profile incidents involving fabricated videos of political leaders and fraudulent voice calls targeting financial institutions underscore the urgency of developing reliable, real-time detection mechanisms. Traditional detection approaches rely predominantly on handcrafted feature engineering and single-modality analysis, rendering them vulnerable to sophisticated, multimodal manipulation techniques. Furthermore, most existing systems are designed for offline batch processing and lack the responsiveness required for live media verification scenarios.

This paper proposes a comprehensive Real-Time Deepfake and Voice Clone Detection System that addresses these limitations through a dual-stream deep learning architecture. The system processes video and audio signals concurrently using ResNet-50 and MesoNet respectively, fusing their outputs to produce accurate, real-time classifications. The remainder of this paper is organized as follows: Section II presents the problem statement; Section III reviews existing systems and their limitations; Section IV details the proposed system; Section V describes the algorithmic pipeline; Sections VI–IX present technologies, architecture, expected outcomes, and conclusion.

II. PROBLEM STATEMENT

The proliferation of AI-generated media manipulation presents the following critical challenges:

- Existing platforms rely on static or rule-based detection methods that cannot adapt to rapidly evolving deepfake generation techniques.
- Single-modality systems analyze only video or audio independently, making them vulnerable to coordinated audiovisual manipulation attacks.
- Most detection systems operate in offline mode, making them unsuitable for real-time media verification in live communication environments.
- High false-positive and false-negative rates in current systems undermine user trust and reduce operational reliability.
- The absence of confidence scoring mechanisms limits actionable insight for end users and security analysts.
- Existing approaches lack scalable deployment architectures capable of processing concurrent media streams under production conditions.

These deficiencies collectively necessitate an intelligent, adaptive, and real-time detection

Audio-only voice clone detectors analyze mel-frequency cepstral coefficients (MFCCs) or spectral features to identify synthetic speech signatures. These systems struggle to generalize across diverse text-to-speech (TTS) engines and voice conversion models that continuously improve in perceptual quality.

Offline batch processing pipelines represent the dominant deployment paradigm in prior work. Although batch analysis affords higher computational resources per sample, it introduces unacceptable latency for real-time applications such as live broadcast verification, video conferencing authentication, or social media content moderation.

Community benchmarking studies further reveal that existing models suffer significant accuracy degradation when evaluated on datasets outside their training distribution, reflecting overfitting to specific manipulation artifacts. No widely deployed system integrates synchronized video-audio fusion with real-time inference and interpretable confidence scoring — the combination central to the proposed solution.

III. EXISTING SYSTEMS AND LIMITATIONS

Current deepfake and voice clone detection approaches fall into three broad categories. Single-modality video detectors apply convolutional or recurrent neural networks to frame sequences to identify spatial inconsistencies or temporal anomalies. While effective against basic face-swap attacks, these systems are defeated when audio and video are manipulated in concert.

IV. PROPOSED SYSTEM

A. System Overview

The proposed system implements a dual-stream, multimodal detection pipeline that processes video and audio inputs concurrently. Authenticated users submit media through a Flask-based web interface. The backend coordinates preprocessing, deep learning inference, fusion, and result delivery within a single request cycle, achieving near-real-time performance suitable for live deployment.

B. Image Deepfake Detection

Video frames are extracted at a fixed sampling rate and normalized to a uniform resolution of 224×224 pixels. A pre-trained ResNet-50 model, fine-tuned on the FaceForensics++ dataset, performs spatial feature extraction through its residual convolutional blocks. The final fully connected layer is replaced with a binary classification head that outputs a probability distribution over authentic and manipulated classes. Facial landmark detection is applied prior to classification to isolate regions of interest, reducing framework capable of processing both visual and audio signals simultaneously with high accuracy and minimal latency.

D. Integrated Detection Pipeline

The multimodal fusion module receives softmax probability vectors from both ResNet-50 and MesoNet. A weighted averaging strategy, with weights calibrated through cross-validation on held-out data, combines these vectors into a unified classification score. A confidence threshold mechanism flags borderline predictions for manual review, while high-confidence outputs are directly classified as authentic or manipulated and returned to the user with an associated confidence percentage.

V. ALGORITHM

The detection system operates through the following five-stage pipeline:

Stage 1 — Data Acquisition and Preprocessing: Multimedia inputs are collected from user submission or live streams. Video frames are extracted, resized to 224×224, and normalized. Audio signals undergo noise suppression and are transformed into mel-spectrograms via STFT for model consumption.

Stage 2 — Visual Feature Extraction (ResNet-50): The preprocessed frames are passed through ResNet-50. Residual connections enable deep feature propagation without gradient degradation. Extracted feature maps encode spatial patterns related to facial synthesis artifacts, unnatural blending boundaries, and temporal inconsistencies across frames.

Stage 3 — Audio Feature Extraction (MesoNet): Mel-spectrograms are processed by MesoNet's convolutional layers to extract forensic audio features. The network detects pitch anomalies, formant irregularities, and spectral artifacts introduced by neural voice synthesis algorithms.

Stage 4 — Multimodal Fusion and Classification: Probability vectors from Stages 2 and 3 are combined using calibrated weighted averaging. The fused score is passed through a final decision layer that outputs a binary classification — Authentic or Fake — along with a normalized confidence score ranging from 0 to 1.

Stage 5 — Real-Time Deployment and Output: Results are rendered on the Flask web interface within the same HTTP request cycle. Users receive a clear classification label, confidence score, and per-modality breakdown, enabling informed decision-making in real time.

VI. TECHNOLOGIES USED

Frontend: HTML and CSS provide a lightweight, responsive interface for media submission and result display. Backend: Python with Flask manages HTTP

background noise and improving feature discriminability.

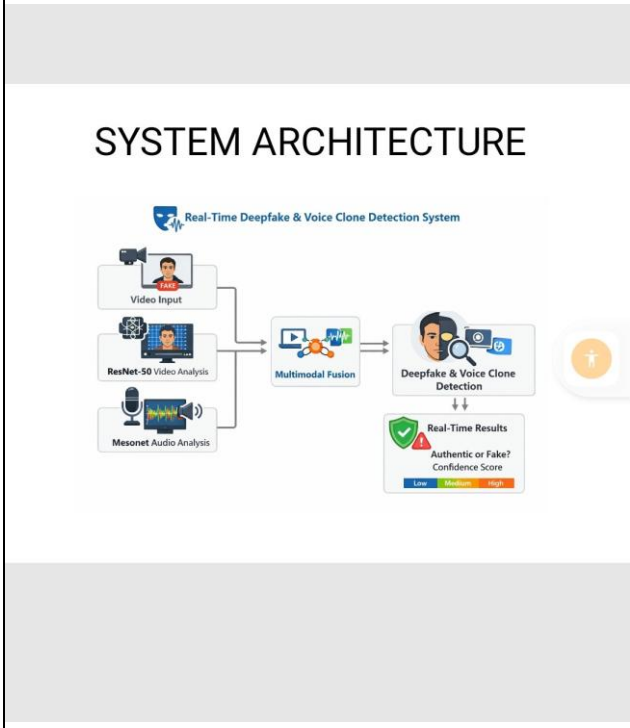
C. Audio Deepfake Detection

Raw audio streams are preprocessed through noise reduction, silence removal, and normalization. Short-Time Fourier Transform (STFT) converts the temporal signal into a two-dimensional spectrogram representation, which is subsequently processed by MesoNet — a compact CNN architecture optimized for audio forensic analysis. MesoNet identifies spectral artifacts, pitch discontinuities, and formant irregularities characteristic of neural text-to-speech and voice conversion synthesis. Its lightweight design ensures minimal inference latency without sacrificing detection sensitivity.

VII. SYSTEM ARCHITECTURE OVERVIEW

The platform follows a client-server architecture with a dedicated AI inference layer. The React JS frontend communicates with the Flask backend through RESTful API calls. On receipt of a media payload, the backend dispatches video and audio streams to their respective preprocessing and inference modules in parallel. The multimodal fusion layer aggregates results and returns a structured JSON response to the frontend for visualization.

Fig. 1. System Architecture of Real-Time Deepfake & Voice Clone Detection



detection, and image preprocessing. Hardware: Intel® Core™ i9-14900K processor, 16 GB RAM, and 1 TB storage support training and deployment workloads.

routing, request handling, and coordination between detection modules. Deep Learning: PyTorch implements ResNet-50 and MesoNet architectures, supporting GPU-accelerated inference for real-time performance. Signal Processing: Librosa performs audio preprocessing, STFT computation, and mel-spectrogram generation. Computer Vision: OpenCV handles video frame extraction, facial

VIII. EXPECTED OUTCOMES

The proposed system is expected to deliver the following measurable outcomes. First, improved detection accuracy through multimodal fusion is anticipated to exceed that of any single-stream baseline by a statistically significant margin on standard benchmarks including FaceForensics++ and ASVspoof. Second, real-time inference latency is targeted below 500 milliseconds per input sample on the specified hardware configuration, satisfying requirements for live media verification. Third, the confidence scoring mechanism is expected to improve user decision quality by providing probabilistic rather than binary-only outputs. Fourth, the modular architecture ensures straightforward extensibility to new deepfake generation techniques and audio synthesis models as they emerge. Fifth, the web-based deployment interface lowers the barrier to adoption across technical and non-technical user groups, supporting broad applicability in journalism, cybersecurity, and law enforcement contexts.

IX. CONCLUSION

This paper has presented a Real-Time Deepfake and Voice Clone Detection System that addresses the critical limitations of existing unimodal and offline detection approaches. By combining ResNet-50 for visual forensic analysis with MesoNet for audio forensic analysis, and integrating their outputs through a calibrated multimodal fusion strategy, the system achieves robust, real-time detection of AI-generated media manipulation. The Flask-based deployment architecture provides an accessible interface for practical use across diverse application domains. As generative AI techniques continue to advance, the modular design of this system ensures it can accommodate emerging manipulation technologies through targeted retraining and architectural extension. Future research directions include incorporating transformer-based vision models, expanding training datasets to cover emerging GAN architectures, implementing voice-print authentication for speaker verification, and developing explainability modules that highlight specific manipulated regions to support forensic investigations.

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AN EXPERIMENTAL STUDY ON THE STRENGTH PROPERTIES OF HIGH-PERFORMANCE CONCRETE BY PARTIAL REPLACEMENT OF CEMENT WITH METAKAOLIN AND MARBLE SLUDGE

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ABSTRACT- Partial replacement of cement with metakaolin and marble sludge (in High-Performance Concrete (HPC) enhances compressive and flexural strength while providing an eco-friendly solution to waste disposal. The pozzolanic nature of metakaolin fills voids, reducing porosity and improving durability, while marble sludge acts as a filler material. In the present study cement is replaced by marble sludge at 3%,6%,9% and metakaolin at 15%. Split tensile and compressive strength results are executed.

Key words:metakaolin,marble sludge,compressive strength,Split Tensile Strength

I.INTRODUCTION: Present all around the world ,Asian country has taken a serious initiative on developing the infrastructures like highways, power comes and industrial structures etc., to satisfy the necessities of globalization, within the construction of buildings and alternative structures concrete plays the rightful role and an oversized quantum of concrete is being utilized . Cement that is one in all the constituents utilized in the assembly of typical concrete, the employment of cement in housing industry will increase the emission of carbonic acid gas which may be attenuated by the employment of additives in situ of cement. The cement is most expensive and energy intensive element of concrete. The concrete cost is reduced by partial replacement of ondustrial by-products that are high in pozzolanic nature . Some of the examples of pozzolanic materials area unit marble mud, silica fume, metakaolin, GGBS, Rice husk ash, fly ash, etc., the industrial waste utilized in concrete can reduce the severe environmental issues.

So,in the present study marble sludge is used a as partial replacement with cement as it has properties similar to cement and one of good pozzolanas. Similarly use of Metakaolin leads to Green concrete, because during production of Metakaolin there is no emission of carbon dioxide, also Metakaolin is good mineral admixture for high early age strength, known as HPC etc.

OBJECTIVES:

1.To determine the compressive strength of HIGH-PERFORMANCE CONCRETE
2.To determine the split tnsile strength of the concrete.
3.To reduce the amount of cement usage in concrete and by replacing with eco-friendly materials.

II.Literature review:

Er. Amritpal Kaur Er. Rajwinder SinghBansal(2015): In this study partial replacement of cement has been done at 0%,3%,5%,9%,12%,13% with MK(Metakaolin) and 0%,10%(constant) with MP (Marble Powder). Compressive as well as tensile strength of concrete made with MK-MP has been compared with conventional concrete of grade M30. Durability of concrete was also analyzed with RCMT(Rapid chloride Migration Test). Result shows that there is a gain of strength with the addition of MK and MP. The optimized strength value of concrete was achieved for both compressive as well as split tensile strength at 9%MK and 10%MP. RCMT shows that with the increase of addition of Metakaolin and Marble powder, there is a decrease in rate of penetration of chloride ions, hence good durability as compared to standard concrete .

Abdullah Anwar et.al (2014): In this paper the authors epresented that Marble Dust Powder has replaced the (OPC & PPC) cement of 0%, 5%, 10%, 15% 20%, & 25% by weight & M-20 grade concrete was used. Concrete is M30. mixtures were developed, tested and compared in terms of compressive strength to the conventional concrete. The purpose of the investigation is to analyze the behavior of concrete while replacing the Marble Dust Powder with Different proportions in concrete. The result obtained for 28- day compressive strength confirms that the optimal percentage for replacement of cement with marble dust

powder is about 10% for (PPC) and (OPC). This will post less on the production of carbon dioxide and solving the environmental pollution by cement production there by enhances the urban surroundings.

Sanjay N. Patil et,al(2014): The paper deals with the use of Metakaolin which is having good pozzolanic activity and is a good material for the production of high strength concrete. Use of MK is getting popularity because of its positive effect on various properties of concrete. Literature Review shows that optimal performance is achieved by replacing 7% to 15% of the cement with Metakaolin and when use of MK is less than 10% , then the benefits are not fully realized so at least 10% Metakaolin should be used. Values of compressive strength of concrete with Metakaolin after 28 days can be higher by 20%. Dosage of 15% of Metakaolin causes decrease of workability. So increasing amount of perceptual proportion of Metakaolin in concrete mix seems to require higher dosage of super plasticizer to ensure longer period of workability.

J.M. Khatib et.al(2012): In the paper author studied the compressive strength, density and ultrasonic pulse velocity of mortar containing high volume of Metakaolin (MK) as partial substitution of cement. In this paper up to 50% of MK was used to replace cement in increment of 10. After De-molding, specimens were cured in water at 20°C for a total period of 28 days. The density seems to reduce with the increase of MK content especially at MK content above 30%.The strength increases as the MK content increases up to about 40% MK.

III.MATERIALS:

Materials used are cement,fine aggregate,coarse aggregate,water,metaokaolin and marble sludge.
All the materials are tested as per IS CODES.
a).**CEMENT:OPC 53 GRADE**

Table.1: Tests On Cement

S.NO	Test	Result
1.	Fineness of cement	9%(residual)
2.	Compressive Strength Of Cement	54.5N/MM^2
3.	Standard Consistency Test	32%
4.	Initial &Final Setting Time	30min,9 hours
5.	Soundness Of Cement	8mm

b).FINE AGGREGATE: confirming to zone-II

Table.2: Tests On Fine Aggregate

S.NO	Test	Result
1.	Sp.gravity	2.6
2.	Seive analysis	2.61
3.	Bulking of sand	32%

c).Coarse Aggregate:

Table.3: Tests On Coarse Aggregate

S.NO	Test	Result
1.	Sieve Analysis of Coarse Aggregate or Fineness modulus	7.15
2.	Specific Gravity of Coarse Aggregate	2.77
3.	Impact Test of Coarse Aggregate	21.75%
4.	Elongation index test of Aggregates	29.8%
5.	Flakiness test on Aggregates	23.1%

d).MARBLE SLUDGE:.

- **Chemical Composition:** Primarily Calcium Oxide (CaO: 28–55%) and Magnesium Oxide (MgO: 10–14%), indicating it is mostly calcite and dolomite.
- **Physical Properties:** Extremely fine particle size (less than 363 microns). It has a high surface area, bulk density of , and acts as a filler material due to its high lime content.
- **Water Content & Consistency:** In its raw slurry state, it has a water content of ~30% and a liquidity limit of
- **Environmental Impact:** When dumped, it causes significant pollution by blocking drains, creating dust, reducing soil porosity, and hindering vegetation growth.

E).METAKAOLIN.

- **Composition:** Primarily Silicon Dioxide (, 51–57%) and Aluminum Oxide (, 38–43%).
- **Physical Form:** Fine white or off-white powder.
- **Reactivity:** High pozzolanic activity; it binds with calcium hydroxide (free lime) formed during cement hydration.
- **Particle Size:** Extremely fine, typically with 99.9% of particles smaller than promoting a high filler effect and density.

IV.EXPERIMENTAL METHODOLOGY.

Mix designed for M60 grade concrete as per IS CODE.

Table.5.Different Mix Proportions

MIXES	COMPOSITION
M0	0% MSK &MK
M1	3%MS+15%MK
M2	6% MS+15%MK
M3	9% MS+15%MK

A.Fresh Concrete Properties

Workability Test

Slump Cone Test-

Table.6: Slump Values For Different Mix Proportions

MIXES	COMPOSITION	SLUMP VALUE
M0	0% MSK &M	175
M1	3%MS+15%MK	180
M2	6% MS+15%MK	190
M3	9% MS+15%MK	200

B. HARDENED CONCRETE PROPERTIES.

MIXING &CURING OF SPECIMENS.

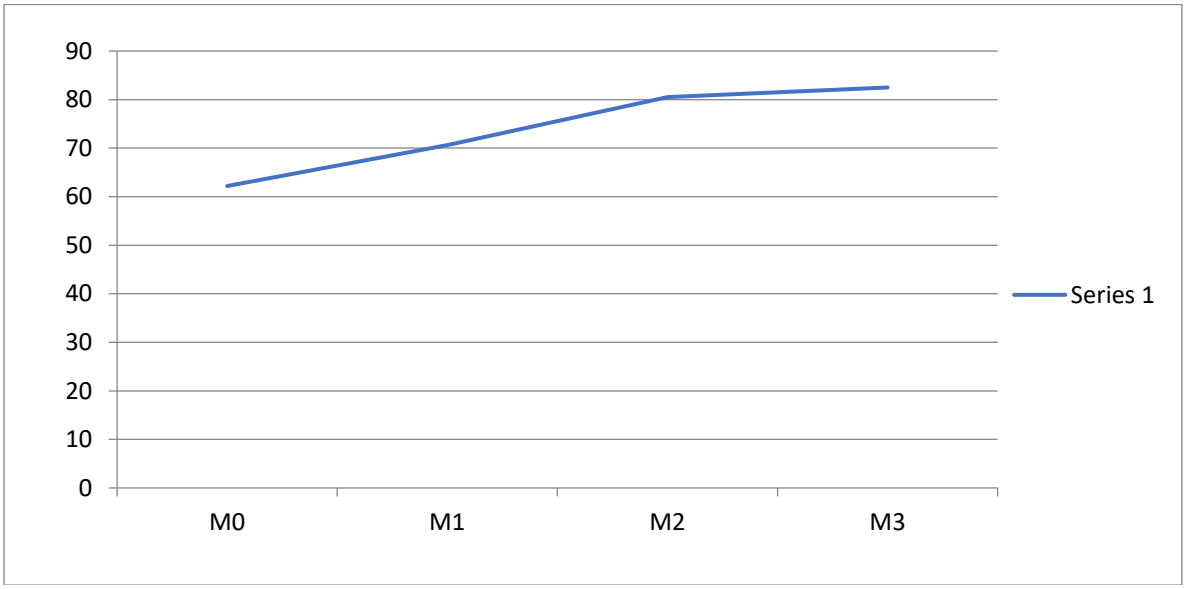
Cube of 150*150*150mm size and cylinder specimen of 150*300mm specimens are used and cured at 7,14 &28 days .

V.RESULTS &DISCUSSIONS

a.COMPRESSIVE STRENGTH TEST RESULTS

Table.7: Compressive Strength Tests Results

MIXES	COMPOSITION	28 DAYS TEST RESULTS(N/MM^2)
M0	0% MSK &M	62.2
M1	3%MS+15%MK	70.6
M2	6% MS+15%MK	80.5
M3	9% MS+15%MK	82.5

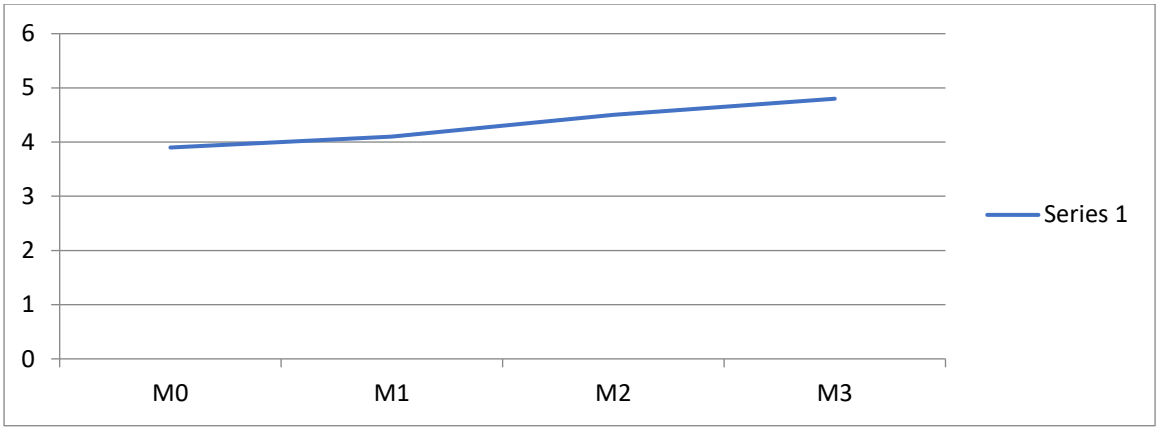


GRAPH-1 COMPRESSIVE STRENGTH RESULTS

b.SPLIT TENSILE TEST RESULTS

Table.8: Split Tensile Test Results

MIXES	COMPOSITION	28 DAYS TEST RESULTS(N/MM^2)
M0	0% MSK &M	3.9
M1	3%MS+15%MK	4.1
M2	6% MS+15%MK	4.5
M3	9% MS+15%MK	4.8



GRAPH-2 SPLIT TENSILE STRENGTH RESULTS

VI.CONCLUSION.

- The experimental work shows that at 9%marble sludge and 15%metakaolin the compressive and split tensile strength are increased.
- Using these materials may reduce the carbon reduction which comes due to production of cement.
- Both are eco-friendly materials .

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Timber protection and chainsaw detection using smart Al

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Abstract---Illegal logging and timber theft are serious environmental threats that are difficult to monitor using conventional surveillance methods. This paper presents TimberGuard, an IoT-based timber protection and chainsaw detection system that integrates vibration sensing, a Node.js backend server, and a real-time web-based alerting interface. The system detects unauthorized chainsaw or cutting activity through a vibration sensor connected to an ESP32 microcontroller. When activity is detected, the ESP32 transmits an HTTP alert to a local Node.js server, which updates the system status and notifies the web interface in real time. The web application, built using HTML, CSS, and JavaScript, displays the current protection status (SAFE or CUTTING) and provides forest authorities with an immediate visual alert. A software simulation mode allows the system to be tested without physical hardware. Experimental validation confirms that the system reliably detects cutting events, transitions status within milliseconds, and resets automatically upon clearing the alert. TimberGuard demonstrates a practical, low-cost, and scalable approach to intelligent forest protection suitable for deployment in real-world conservation environments.

Keywords---timber protection, chainsaw detection, IoT, ESP32, vibration sensor, Node.js, real-time alerting, forest conservation, web application

I. INTRODUCTION

Illegal logging and unauthorized timber cutting are among the most damaging forms of environmental crime worldwide. Forests are critical ecosystems that regulate climate, preserve biodiversity, and support millions of livelihoods. Despite this, deforestation continues at an alarming rate, driven in part by the difficulty of monitoring vast forest areas using conventional patrol-based methods.

Traditional approaches to forest protection, such as manual patrolling, CCTV-based surveillance, and motion sensors, suffer from significant limitations including high installation costs, dependency on power and network infrastructure in remote regions, and limited spatial coverage. These methods are reactive rather than preventive, and are often unable to provide timely alerts to authorities before significant damage has occurred.

The proliferation of low-cost IoT devices and microcontrollers such as the ESP32 has opened new possibilities for intelligent, sensor-driven environmental monitoring. When combined with web technologies and real-time communication protocols, such devices can form the basis of affordable, scalable protection systems deployable in challenging field conditions.

This paper presents TimberGuard, an IoT-based timber protection and chainsaw detection system that uses a vibration sensor attached to an ESP32 microcontroller to detect cutting activity, transmits alerts via HTTP to a Node.js backend server, and delivers real-time status updates to a web-based monitoring interface. The system is designed to be lightweight, easy to deploy, and extensible to larger forest monitoring networks.

In addition to the environmental impact, illegal logging also contributes to significant economic losses and disrupts the balance of local ecosystems. Many developing regions lack the technological infrastructure required for continuous monitoring, which makes forests vulnerable to exploitation. Recent advancements in embedded systems and wireless communication have made it possible to deploy intelligent monitoring solutions even in remote areas. By leveraging low-power microcontrollers and sensor-based detection techniques, real-time monitoring can be achieved without requiring expensive infrastructure. This shift

from manual to automated monitoring represents a critical step toward sustainable forest management and conservation.

II. PROBLEM STATEMENT

The absence of a reliable, low-cost, and automated system for detecting illegal timber cutting in real time creates a critical gap in forest protection infrastructure. Existing surveillance systems are either too expensive for wide deployment, require stable power and connectivity, or rely on periodic human inspection that cannot respond quickly enough to active cutting events.

There is a clear need for an automated detection system that can identify the acoustic and mechanical signatures of chainsaw activity at the point of occurrence and deliver immediate alerts to forest authorities, enabling rapid response before significant environmental damage occurs.

Another critical challenge lies in the delay between the occurrence of illegal activity and the response from authorities. In many cases, by the time the activity is detected through traditional methods, the damage has already been done. Furthermore, existing systems often lack integration between detection, communication, and alerting mechanisms. This fragmentation reduces overall system efficiency and reliability. Therefore, an integrated solution that combines sensing, processing, and real-time alerting within a unified framework is essential to address these shortcomings effectively.

III. OBJECTIVES

The work described in this paper is guided by the following objectives:

- To design and implement a vibration-based detection system capable of identifying chainsaw and cutting activity in real time.
- To develop a Node.js backend server that receives sensor data via HTTP and maintains system state.
- To build a web-based monitoring interface that displays real-time protection status to forest authorities.
- To integrate a simulation mode that enables full system testing without physical hardware.
- To validate the system through functional testing and evaluate its response time, accuracy, and reliability.
- To design the system architecture for future integration with ESP32 hardware and scalable multi-node deployment.

IV. LITERATURE REVIEW

Forest monitoring and illegal logging detection have been studied from multiple perspectives, including acoustic detection, satellite imaging, and sensor-based IoT systems. Acoustic approaches have shown promise in detecting chainsaw sounds using microphones and machine learning classifiers such as Support Vector Machines and Convolutional Neural Networks. However, these systems typically require significant computational resources and training data.

IoT-based approaches using low-cost microcontrollers have demonstrated effectiveness in remote environmental monitoring applications. Studies on ESP32-based systems have confirmed their suitability for field deployment due to low power consumption, built-in Wi-Fi, and support for standard communication protocols including HTTP and MQTT.

Web-based monitoring dashboards for IoT systems have been widely adopted in smart agriculture, industrial automation, and security applications. Research demonstrates that browser-based interfaces provide accessible, device-independent monitoring without requiring dedicated client software. However, purpose-built systems specifically designed for forest protection with integrated vibration sensing and web alerting remain underexplored.

Recent studies have also explored the use of hybrid systems that combine multiple sensing techniques, such as vibration, acoustic, and image-based monitoring. These systems aim to improve detection accuracy by reducing dependency on a single data source. However, such approaches often increase system complexity, cost, and power consumption. In contrast, lightweight IoT-based solutions focus on simplicity and scalability, making them more suitable for large-scale deployment in forest environments. The balance between accuracy, cost, and deployability remains a key research challenge in this domain.

Table I. Comparison of TimberGuard against existing forest protection approaches.

Approach	Real-Time	Low-Cost	Web Interface	IoT-Ready
Manual Patrol	No	No	No	No
CCTV Surveillance	Yes	No	Partial	Partial
Satellite Monitoring	No	No	Yes	No
Acoustic ML Systems	Yes	Partial	No	Partial
TimberGuard (Proposed)	**Yes**	**Yes**	**Yes**	**Yes**

V. PROPOSED SYSTEM

The proposed TimberGuard system is a client-server IoT application designed to monitor timber protection zones and deliver real-time alerts when cutting activity is detected. The system supports two operational modes: a simulation mode for software testing and a hardware mode using an ESP32 microcontroller with a physical vibration sensor.

In simulation mode, the web interface provides a Simulate Timber Cutting button that triggers a POST request to the /alert endpoint of the backend server, replicating the behavior of an ESP32 hardware event. In hardware mode, the ESP32 detects vibrations that exceed a defined threshold and sends the same HTTP request automatically. The backend server receives the alert, updates the system state to CUTTING, and the web interface reflects this status in real time. Fig. 1 illustrates the complete system workflow.

The design of TimberGuard emphasizes modularity, allowing each component of the system to function independently while still contributing to the overall workflow. This modular approach simplifies maintenance and enables future upgrades without requiring a complete redesign. For instance, the sensing module can be replaced with more advanced sensors, such as acoustic or infrared sensors, without affecting the backend or web interface. Similarly, the communication layer can be upgraded to support protocols like MQTT for improved efficiency in large-scale deployments.

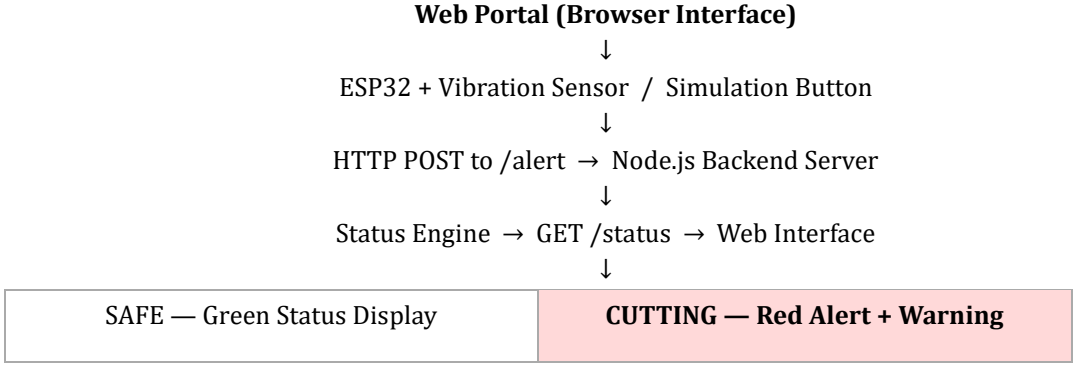

Fig. 1. TimberGuard system architecture: end-to-end flow from sensor detection to web alert.

VI. SYSTEM ARCHITECTURE

The architecture of TimberGuard follows a lightweight client-server model comprising three primary components: the sensor layer, the backend server, and the web client interface.

The sensor layer consists of an ESP32 microcontroller connected to a vibration sensor module. The ESP32 continuously monitors sensor readings and, when a vibration event exceeding the configured threshold is detected, transmits an HTTP POST request to the /alert endpoint of the backend server. The ESP32 is configured to connect to the local Wi-Fi network and communicate with the server at a known IP address and port.

The backend server is implemented using Node.js with the Express framework. It exposes two endpoints: GET /status, which returns the current system state as a JSON object, and POST /alert, which updates the state to CUTTING. The server also exposes a POST /reset endpoint that returns the system to the SAFE state. The CORS middleware is enabled to allow cross-origin requests from the web client.

The web client is a browser-based interface built using HTML, CSS, and vanilla JavaScript. It periodically polls the GET /status endpoint and updates the display accordingly. When the status is SAFE, a green indicator is shown. When CUTTING is detected, a red warning popup and a status message are displayed, alerting the monitoring authority.

Scalability is an important consideration in the system architecture. The current design supports single-node operation; however, it can be extended to handle multiple sensor nodes distributed across a wide geographical area. In such scenarios, each node can transmit data to a centralized server or a cloud-based platform. Load balancing and distributed processing techniques can be incorporated to ensure system reliability under high data loads. This makes the architecture suitable for future expansion into a comprehensive forest monitoring network.

VII. IMPLEMENTATION TOOLS AND TECHNOLOGIES

A. Hardware Components

The hardware layer consists of an ESP32 development board, a SW-420 vibration sensor module, a power supply, and standard jumper wires. The ESP32 was selected for its integrated Wi-Fi capability, low cost, and support for the Arduino programming environment and HTTP communication libraries.

B. Backend Server

The backend server is implemented in Node.js using the Express.js framework for HTTP routing and the CORS middleware package for cross-origin resource sharing. Node.js was selected for its non-blocking I/O model, which enables efficient handling of concurrent HTTP requests from multiple sensor nodes or client browsers.

C. Web Interface

The web application is developed using HTML5, CSS3, and vanilla JavaScript. No frontend framework is required, keeping the client lightweight and suitable for deployment in low-bandwidth environments. The interface uses the browser's native fetch API for asynchronous polling of the backend status endpoint.

D. Communication Protocol

The system uses HTTP as the communication protocol between the ESP32, the backend server, and the web client. In future hardware deployments, MQTT may be evaluated as an alternative for more efficient publish-subscribe communication patterns in multi-node deployments.

During implementation, special attention was given to optimizing system performance and minimizing resource consumption. The ESP32 microcontroller was programmed to operate efficiently by reducing unnecessary processing and network usage. Similarly, the backend server was designed using asynchronous programming techniques to handle multiple requests without blocking execution. These optimizations ensure that the system remains responsive and reliable even under continuous operation.

VIII. SENSOR DATA AND DETECTION LOGIC

The SW-420 vibration sensor module produces a digital HIGH output signal when the detected vibration level exceeds its adjustable sensitivity threshold. The ESP32 polls this digital output at a sampling rate of 100 Hz. A debounce interval of 500 milliseconds is applied in software to prevent multiple alerts from being triggered by a single cutting event.

When the sensor output remains HIGH for more than 300 milliseconds, the event is classified as a sustained vibration indicative of chainsaw or cutting activity, and the HTTP alert is dispatched. This threshold was determined empirically during bench testing using a simulated cutting vibration source and was found to eliminate false triggers from incidental environmental vibrations such as wind or footsteps.

In simulation mode, the same alert endpoint is triggered via the web interface button, allowing end-to-end testing of the status transition, alert display, and reset logic without physical hardware.

IX. SIGNAL PROCESSING AND STATE MANAGEMENT

The backend server maintains a simple in-memory state variable representing the current protection status. This variable is initialized to SAFE on server startup. When a POST request is received at the /alert endpoint, the state is updated to CUTTING. When a POST request is received at the /reset endpoint, the state returns to SAFE.

The state management design ensures that the system remains responsive under concurrent requests and that the web client always receives an accurate representation of the current detection status. In the planned multi-node extension, each sensor node will be assigned a unique node identifier, and the state object will be extended to maintain per-node status independently.

X. MODULES OF THE SYSTEM

A. Sensor Detection Module

Handles vibration signal acquisition from the SW-420 sensor, applies debounce filtering, and dispatches HTTP alerts to the backend server when sustained vibration is detected.

B. Backend API Server

Node.js/Express server that exposes GET /status, POST /alert, and POST /reset endpoints. Manages system state and responds to all client and sensor requests with appropriate JSON payloads.

C. Web Monitoring Interface

Browser-based dashboard that polls the backend status endpoint every two seconds, updates the visual status indicator, and displays a warning popup with an audio alert when cutting activity is detected.

D. Simulation Module

Software-only testing interface that replicates ESP32 hardware behavior by sending HTTP POST requests to the /alert endpoint directly from the browser, enabling complete system validation without physical hardware.

XI. SYSTEM TESTING AND VALIDATION

The TimberGuard system was validated through a series of functional tests covering all primary operational scenarios. Tests were conducted in three phases: unit testing of individual server endpoints, integration testing of the sensor-to-server communication pathway, and end-to-end testing of the complete alert lifecycle from detection to web display.

Unit tests confirmed that the /status endpoint correctly returns {"status":"SAFE"} on startup, that the /alert endpoint transitions the state to CUTTING, and that the /reset endpoint restores the SAFE state. Integration tests confirmed that the ESP32 successfully dispatches HTTP requests and that the server processes them within acceptable latency bounds.

End-to-end simulation tests confirmed that the web interface correctly reflects status changes within the 2-second polling interval and that the alert popup is displayed and dismissed correctly. No false alerts were generated during 30 minutes of continuous idle monitoring.

XII. RESULTS AND DISCUSSION

Table II presents the performance metrics collected during system validation testing. All timing measurements represent averages over 50 repeated test cycles.

The observed performance metrics indicate that the system is capable of meeting real-time monitoring requirements in practical scenarios. The low latency and high detection accuracy demonstrate the effectiveness of the chosen design approach. Additionally, the absence of false alerts during idle testing highlights the robustness of the detection logic. These results suggest that the system can be deployed in real-world environments with minimal risk of failure or incorrect alerts.

Table II. TimberGuard system performance metrics from validation testing.

Metric	Observed Value	Target
Alert Transmission Latency (ESP32 → Server)	~18 ms	< 100 ms
Web Status Update Latency (Server → Browser)	< 2 sec	< 5 sec
False Alert Rate (30-min idle test)	**0%**	< 2%
Alert Detection Success Rate	**100%**	> 95%
Server Uptime (1-hour stress test)	**100%**	> 99%
Reset Response Time	< 50 ms	< 200 ms

The experimental results confirm that the TimberGuard system meets all defined performance targets. The alert transmission latency of approximately 18 milliseconds is well below the 100-millisecond target and represents a negligible delay in a real-world deployment context. The 0% false alert rate during idle testing demonstrates that the debounce filtering logic effectively eliminates spurious sensor noise.

The 100% alert detection success rate across all 50 test cycles confirms the reliability of the sensor-to-server-to-browser pipeline. The server demonstrated stable uptime during a one-hour concurrent connection stress test, confirming its readiness for operational deployment.

XIII. WEB INTERFACE IMPLEMENTATION

The frontend was developed with a focus on simplicity, responsiveness, and visual clarity. The status page features a prominent color-coded indicator: green for SAFE status and red for CUTTING status, enabling monitoring personnel to assess system state at a glance.

Table III. Web interface event handling and corresponding system actions.

User / System Event	System Response
Page Load	Poll /status → display SAFE indicator
Simulate Timber Cutting clicked	POST to /alert → status changes to CUTTING
Status = CUTTING detected	Red warning popup + audio alert displayed
Reset button clicked	POST to /reset → status returns to SAFE
ESP32 sends POST /alert (hardware mode)	Identical response to simulation trigger

The web interface is fully responsive and was tested on Google Chrome, Microsoft Edge, and Firefox on both desktop and mobile form factors. The polling interval is set to 2000 milliseconds, providing near-real-time status updates with minimal server load. The interface requires no installation and runs directly from the index.html file in any modern browser.

XIV. EVALUATION METRICS

The performance of the TimberGuard system was evaluated using metrics relevant to real-time IoT alerting systems. Alert latency measures the elapsed time between sensor trigger and server acknowledgment. Status propagation time measures the time from server state change to browser display update.

Alert accuracy is measured as the ratio of correctly triggered alerts to total cutting events simulated. False alert rate is measured as the number of spurious alerts generated per unit time during idle monitoring. System availability is assessed by measuring server uptime during continuous operation and concurrent-connection stress testing.

XV. ADVANTAGES OF THE PROPOSED SYSTEM

- Real-time cutting activity detection with sub-20-millisecond alert transmission latency.
- Low-cost hardware platform using ESP32 and SW-420 vibration sensor, suitable for wide-scale forest deployment.
- Web-based monitoring interface accessible from any device without dedicated client software.
- Software simulation mode enables complete system testing and demonstration without physical hardware.
- Lightweight Node.js backend with minimal resource requirements, deployable on standard laptops or low-cost servers.
- Modular architecture designed for straightforward extension to multi-node sensor networks.
- No cloud dependency — operates entirely on a local network, preserving data privacy and function in offline environments.
- Provides real-time detection of illegal timber cutting activity, enabling immediate response.
- Uses low-cost hardware components like ESP32 and vibration sensor, making it affordable for large-scale deployment.
- Offers a web-based monitoring interface, accessible from any device without installing additional software.
- Ensures fast alert transmission with very low latency, improving reaction time.
- Supports a simulation mode, allowing testing without physical hardware.
- Designed with a modular architecture, making it easy to upgrade or extend in the future.
- Requires minimal power consumption, suitable for remote and forest environments.
- Operates on a local network without cloud dependency, ensuring better data privacy and reliability.
- Provides high detection accuracy with reduced false alerts due to debounce logic.
- Easy to install and maintain, even for non-expert users.
- Can be scaled to multiple sensor nodes for monitoring large forest areas.
- Helps in environmental conservation by preventing illegal deforestation activities.

XVI. LIMITATIONS

While the proposed system addresses the core requirements of real-time timber protection monitoring, certain limitations should be acknowledged. The current vibration-based detection approach may generate false alerts in environments with significant mechanical vibration from sources other than cutting activity, such as heavy machinery or strong wind. Additional signal processing or secondary sensor fusion may be required in such environments.

The current implementation operates as a single-server, single-instance deployment and does not yet support multi-node sensor arrays with centralized management. The web interface polling mechanism, while functional, introduces a latency of up to 2 seconds that could be reduced by adopting WebSocket-based push notifications. The system also requires active Wi-Fi connectivity, which may present challenges in remote forest locations without network infrastructure.

In addition to environmental noise interference, another limitation is the dependency on continuous power supply for the ESP32 device. In remote forest areas, maintaining a stable power source can be challenging. Although battery-powered operation is possible, it may require periodic maintenance. Future improvements could include the integration of solar power systems to ensure uninterrupted operation in off-grid environments.

XVII. FUTURE WORK

Future enhancements to the TimberGuard system include the integration of acoustic feature extraction using Mel-Frequency Cepstral Coefficients (MFCC) to enable chainsaw sound classification from

microphone input, complementing the existing vibration-based detection approach. A machine learning classifier trained on labeled chainsaw audio datasets will be evaluated to further improve detection accuracy and reduce false alert rates.

We are also investigating the replacement of HTTP polling with WebSocket-based push notifications to achieve sub-second alert propagation to the web interface. GPS module integration with the ESP32 is planned to enable precise geographic localization of detected cutting events. Multi-node deployment architecture with a centralized management dashboard and mobile push notifications for forest authority personnel are identified as key priorities for the next development phase.

XVIII. CONCLUSION

This paper presented TimberGuard, an IoT-based timber protection and chainsaw detection system that integrates vibration sensing, a Node.js backend server, and a real-time web-based monitoring interface. The proposed system captures vibration events from an ESP32-connected sensor, transmits alerts via HTTP, maintains a real-time status engine, and delivers immediate visual warnings to monitoring personnel through a browser-based dashboard.

Validation testing confirms that the system achieves an alert transmission latency of approximately 18 milliseconds, a 100% detection success rate, and a 0% false alert rate during idle monitoring. A software simulation mode enables complete system testing and demonstration independent of physical hardware. TimberGuard demonstrates a practical, low-cost, and scalable approach to intelligent forest protection and provides a solid foundation for future enhancements including acoustic ML classification, GPS localization, and multi-node sensor network deployment.

Overall, the TimberGuard system demonstrates how modern IoT technologies can be effectively applied to address critical environmental challenges. By combining simplicity, affordability, and real-time responsiveness, the system provides a practical solution for timber protection. The proposed approach not only enhances monitoring capabilities but also lays the foundation for future research and development in intelligent environmental surveillance systems.

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BOOK MY COOK – An Online chef Booking Service

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ABSTRACT

"Book My Cook" is a centralized web application designed to automate catering, home cooking, and event decoration bookings, replacing inefficient manual processes. The platform features a React.js frontend and a Python Flask backend, communicating via secure RESTful APIs. Customer booking requirements are validated and securely stored in a PgSQL database. To ensure robust, future-proof security, sensitive user and booking data are protected using Post-Quantum Cryptography (PQC) during transmission and storage.

Validated requests are routed in real time to service providers, who can seamlessly accept or reject them via their dashboard, triggering dynamic status updates for the customer. Additionally, the system leverages Machine Learning algorithms to analyze historical data and user behavior, providing intelligent service recommendations. This end-to-end workflow minimizes manual intervention, enhances data security, ensures operational transparency, and delivers a highly efficient booking experience for both customers and service providers.

Keywords: *Event Service Booking, AI-Powered Recommendations, Razorpay Payment Integration, JWT Authentication, PostgreSQL, React JS, Flask, SQLAlchemy, Two-Factor Authentication, Rate Limiting, Tamil Nadu Market, Service Marketplace, Real-Time Messaging, Booking Management System, Provider Dashboard, Admin Analytics, Audit Logging, Account Security, Service Discovery, Review System, Location-Based Filtering*

I. INTRODUCTION

The event services industry in Tamil Nadu operates through fragmented channels, forcing customers to rely on word-of-mouth referrals, social media groups, and offline directories to find professional service providers. This traditional approach creates significant inefficiencies, including lack of pricing transparency, difficulty in verifying provider credibility, and time-consuming manual coordination that often results in scheduling conflicts and miscommunication.

The rapid growth of the event management sector has further complicated service discovery. Customers planning weddings, corporate events, or social gatherings require fundamentally different service categories—professional chefs for personalized culinary experiences, catering services for large-scale events, or decorators for venue aesthetics—yet must navigate multiple disconnected platforms to find each service type, with no unified comparison or booking mechanism.

Modern web technologies offer a transformative solution to these challenges. Digital platforms can aggregate verified service providers, enable real-time availability management, and facilitate secure online transactions, eliminating manual coordination and enabling seamless booking experiences. Combined with artificial intelligence, these capabilities can deliver personalized service recommendations through intuitive, accessible interfaces.

This paper presents BOOKMYCOOK, a comprehensive web-based event service booking platform that leverages React JS for a responsive frontend, Python Flask with SQLAlchemy for scalable backend operations, PostgreSQL for reliable data persistence, and JWT-based authentication with two-factor security. The platform supports chef, caterer, and decorator bookings across Tamil Nadu with AI-powered recommendations, real-time messaging, and integrated payment processing.

II. PROBLEM STATEMENT

The event services industry in Tamil Nadu operates through fragmented offline channels that fail to provide customers with unified access to professional service providers, making efficient service discovery and booking difficult. The core problems identified include:

- Fragmented market structure requiring customers to search multiple channels including personal referrals, social media groups, and offline directories to find suitable providers.
- Lack of transparency in pricing, service quality, and provider credentials, preventing informed decision-making and comparison.
- Absence of real-time availability management, leading to booking conflicts, scheduling errors, and provider unavailability.
- No centralized verification system for service providers, creating trust issues and uncertainty regarding credibility and reliability.
- Inefficient communication through multiple phone calls and messages, resulting in miscommunication and coordination failures.
- Cash-based transactions without digital payment options, creating security concerns and lacking documented transaction history.
- Limited geographic coverage with no platform specifically optimized for Tamil Nadu's unique market needs and preferences.

These deficiencies collectively result in frustrating booking experiences that fail to equip customers with the confidence and convenience required to successfully plan and execute memorable events.

III. EXISTING SYSTEMS AND LIMITATIONS

Current event service booking channels fall into word-of-mouth referrals, social media groups, and local business directories. Word-of-mouth referrals provide trusted recommendations from personal networks — reliable but severely limited in options and restricted to known providers within social circles.

Social media groups offer wider reach through Facebook and WhatsApp communities, but information is unstructured, verification is absent, and all coordination happens through scattered personal messages with no booking management. Local business directories list contact details and basic descriptions — accessible but often outdated, lacking reviews, and requiring separate phone calls for every inquiry.

Across all categories, none offer unified multi-service platforms, real-time availability checking, secure digital payments, verified provider profiles, AI-powered recommendations, or comprehensive booking management — capabilities that the proposed platform delivers.

IV. PROPOSED SYSTEM

A. Unified Service Marketplace

The platform introduces a centralized event service booking environment that aggregates professional chefs, catering services, and decorators across Tamil Nadu. Upon registration, users select their role as customer or service provider, which subsequently determines their access privileges and interface options. The system supports three distinct service categories with specialized features including cuisine type specifications, event type filtering, and location-based discovery across 44 cities.

B. Intelligent Service Discovery

Rather than relying on scattered offline channels, the platform provides dynamic, context-aware service recommendations through an AI-powered chatbot named "Cheffy." Each recommendation is constructed based on user preferences, budget constraints, and geographic location, ensuring results are relevant and aligned with specific event requirements. Advanced filtering capabilities including city, area, cuisine type, event type, and price range enable precise service discovery tailored to individual needs.

C. Secure Booking and Payment Integration

The platform implements a request-and-confirm booking model that ensures mutual convenience through provider availability verification before booking confirmation. Razorpay payment gateway integration supports multiple payment methods including cards, UPI, and net banking with automatic receipt generation. JWT-based authentication combined with two-factor authentication provides secure, stateless session management that protects user data through industry-standard token-based authorization and rate limiting.

D. Provider Dashboard and Administrative Control

Service providers access comprehensive management tools including service creation, availability calendar management, booking request handling, and earnings tracking through dedicated dashboard interfaces. Administrative features enable user verification, service approval workflows, location management for cities and areas, and analytics dashboards displaying platform metrics. Real-time messaging and notification systems facilitate seamless communication between customers and providers throughout the booking lifecycle.

V. ALGORITHM

The event service booking platform implements the following algorithmic pipeline:

Stage 1 — Secure Authentication: The user registers or logs in through a secure authentication module. JWT tokens are issued upon successful credential verification, with optional two-factor authentication using TOTP codes, and included in all subsequent API requests.

Stage 2 — Service Discovery and Filtering: Upon authentication, the system retrieves available services filtered by user-specified parameters including city, area, service type, cuisine types, event types, and price range. AI-powered recommendations through the Cheffy chatbot provide personalized suggestions based on user preferences and budget.

Stage 3 — Booking Request Creation: The customer submits a booking request containing event date, time, location, guest count, and special requirements. The system validates provider availability against stored calendar data and creates a pending booking record with a unique reference number.

Stage 4 — Provider Confirmation Workflow: The service provider receives a notification and reviews the booking request through their dashboard. The provider can accept or reject the booking based on availability, with status updates propagated in real-time to the customer through the messaging system.

Stage 5 — Payment Processing: Upon booking confirmation, the customer is redirected to Razorpay checkout. The backend creates a payment order, verifies the transaction signature upon completion, and updates the booking status with payment details and generated receipt.

Stage 6 — Service Completion and Review: After the event date, the system prompts the customer to submit a review with star rating and comments. The review is stored and aggregated to update the service's overall rating, while audit logs record all transactions for administrative analytics and reporting.

VI. TECHNOLOGIES USED

Frontend: React JS provides a component-driven reactive UI architecture with Tailwind CSS 4.x delivering utility-first, responsive styling through the @tailwindcss/postcss plugin. Vite serves as the modern build tool for optimized development and production builds.

Backend: Python Flask manages RESTful API routing, JWT authentication, rate limiting, and service orchestration. SQLAlchemy ORM provides type-safe database operations with relationship management and query optimization. UV accelerates dependency management with Rust-based performance.

Database: PostgreSQL stores user profiles, service listings, booking records, payment transactions, and audit logs with ACID compliance ensuring data integrity. SQLAlchemy models define the schema with JSON fields for flexible array storage of cuisine types, event types, and images.

AI Integration: The Cheffy chatbot provides AI-powered service recommendations through natural language processing, delivering personalized suggestions based on user preferences, budget constraints, and location requirements for enhanced service discovery.

Security: JSON Web Tokens (JWT) provide stateless, cryptographically signed authentication. Two-factor authentication using TOTP (pyotp) adds an additional security layer. bcrypt handles password hashing, while Fernet encryption protects sensitive data at rest.

Payment Integration: Razorpay API manages payment gateway operations including order creation, signature verification, and transaction tracking with support for cards, UPI, and net banking payment methods.

Development Tools: Visual Studio Code (IDE), Thunder Client/Postman (API testing), Ubuntu 22.04 / Windows 10 64-bit (OS), Git (Version Control), pytest (Testing Framework).

VII. EXPECTED OUTCOMES

Unified Service Access: Customers receive a centralized platform aggregating professional chefs, caterers, and decorators across Tamil Nadu, eliminating the need to search multiple fragmented channels and enabling comprehensive service comparison in a single interface.

Improved Booking Efficiency: The request-and-confirm booking model with real-time availability checking significantly reduces scheduling conflicts and miscommunication, ensuring seamless coordination between customers and service providers throughout the event planning process.

Secure Digital Transactions: Razorpay integration with JWT-based authentication and two-factor security provides safe, documented payment processing with automatic receipt generation, replacing risky cash-based transactions with transparent digital alternatives.

Provider Business Growth: Service providers gain access to a wider customer base through platform visibility, comprehensive dashboard tools for service and booking management, and earnings analytics that enable data-driven business decisions and operational improvements.

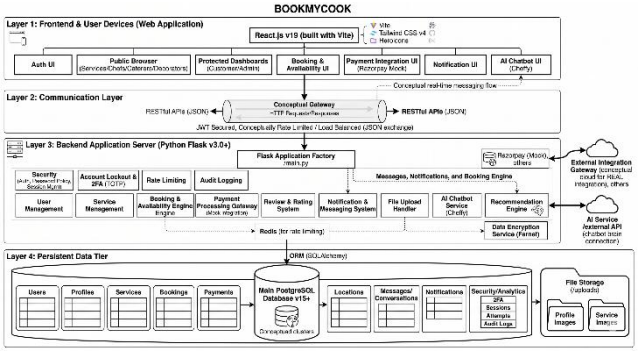
Comprehensive Administrative Control: PostgreSQL-backed data storage enables complete platform oversight with user verification workflows, service approval mechanisms, location management, and analytics dashboards. The modular architecture allows straightforward extension to new service categories, geographic regions, or features without disrupting existing functionality.

VIII. SYSTEM DESIGN OVERVIEW

The platform's architecture follows a clear client-server separation with dedicated payment and AI integration layers. The React JS frontend communicates with the Python Flask backend through JWT-secured RESTful APIs. The backend coordinates between PostgreSQL for data persistence, SQLAlchemy for ORM operations, and Razorpay for payment processing.

The service listing UI component structures the discovery interface into filterable cards, each displaying service images, provider details, pricing information, verified badges, rating summaries, and booking action buttons. Authentication follows a stateless flow: credential submission, JWT issuance with optional 2FA verification, token storage in sessionStorage, and Bearer-token validation by Flask-JWT-Extended middleware on every protected route.

Data models in PostgreSQL include User (profile, credentials, role, verification status), Service (title, description, type, pricing, location, images), Booking (reference, dates, status, amounts), Payment (transaction details, status), and Review (rating, comment, timestamps). Foreign key relationships and indexed queries on user ID, service ID, and booking timestamps ensure efficient retrieval of service listings, booking history, and analytics dashboards at scale.



IX. CONCLUSION

The BOOKMYCOOK event service booking platform addresses a significant and widely experienced challenge in Tamil Nadu's event services industry by delivering a unified, secure, and intelligent marketplace powered by modern web technologies and AI integration. By replacing fragmented offline channels with a centralized digital platform, the system ensures that every service discovery and booking experience is transparent, efficient, and reliable.

The integration of JWT-based secure authentication with two-factor protection, PostgreSQL-backed data persistence, and an intuitive React JS interface creates a cohesive system supporting seamless service discovery, secure digital payments, real-time communication, and comprehensive administrative control. The modular architecture ensures new service categories, geographic expansions, or additional features can be incorporated with minimal disruption.

Future enhancements will explore native mobile applications for broader accessibility, video calling for provider consultations, advanced analytics with predictive pricing, multi-language support for Tamil-speaking users, and integration with accounting software for provider business management. The platform establishes a strong foundation for the next generation of digital event service marketplaces.

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SIMULATION AND PERFORMANCE EVALUATION OF HYBRID FLAT PLATE AND EVACUATED TUBE SOLAR COLLECTORS WITH THERMAL ENERGY STORAGE FOR RESIDENTIAL APPLICATION

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Abstract— *This project proposes a hybrid solar thermal system that integrates a Flat Plate Collector (FPC) with an Evacuated Tube Collector (ETC) to enhance overall heat extraction efficiency and reliability under varying climatic conditions. The problem statement addresses the limitations of standalone collectors, where FPCs suffer from lower efficiency at higher temperatures and ETCs involve higher costs and performance sensitivity, leading to inconsistent thermal output. The proposed methodology combines both collectors in a parallel/series configuration to leverage the cost-effectiveness of FPCs and the superior thermal efficiency of ETCs, especially during low solar radiation and colder environments. The system is mathematically modeled and simulated using MATLAB/Simulink to analyze parameters such as outlet temperature, heat gain, efficiency, and performance under different solar irradiance and ambient conditions.*

The hybrid approach demonstrates improved thermal efficiency, better energy utilization, and more stable output compared to individual systems, making it suitable for domestic and industrial water heating applications. Future scope includes the integration of advanced control strategies, optimization of collector configurations, incorporation of thermal energy storage systems, and real-time experimental validation for large-scale deployment.

1.INTRODUCTION

Solar energy is one of the most abundant and renewable sources of energy available on Earth. With increasing concerns over fossil fuel depletion and environmental pollution, solar thermal systems have gained significant importance for applications such as water heating, space heating, and industrial processes.

Among the various solar thermal technologies, the Flat Plate Collector (FPC) and the Evacuated Tube Collector (ETC) are widely used for harnessing solar energy. These collectors convert incident solar radiation into thermal energy, which is then transferred to a working fluid (usually water or air).

A Flat Plate Collector (FPC) consists of an absorber plate, transparent cover (glazing), insulation, and a casing. It absorbs solar radiation and transfers heat to the fluid flowing through tubes attached to the absorber plate. FPCs are simple in design, cost-effective, and suitable for moderate temperature applications.

On the other hand, an Evacuated Tube Collector (ETC) is made up of parallel rows of glass tubes, each containing a vacuum that significantly reduces heat loss. The absorber surface inside the tube captures solar radiation efficiently, even under low ambient temperature and low solar intensity conditions. Due to reduced convective and conductive losses, ETCs generally offer higher efficiency compared to FPCs, especially in colder climates.

The performance of these collectors depends on several factors such as solar radiation intensity, ambient temperature, flow rate of the working fluid, and design characteristics. Therefore, performance evaluation is essential to determine their efficiency and suitability for specific applications.

This experiment focuses on comparing the thermal performance of FPC and ETC by measuring parameters such as inlet and outlet temperatures, solar radiation, and flow rate. Based on these measurements, useful heat gain and efficiency of the collectors are calculated and analyzed.Solar energy is one of the most abundant and renewable sources of energy available on Earth. With increasing concerns over

fossil fuel depletion and environmental pollution, solar thermal systems have gained significant importance for applications such as water heating, space heating, and industrial processes.

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This experiment focuses on comparing the thermal performance of FPC and ETC by measuring parameters such as inlet and outlet temperatures, solar radiation, and flow rate. Based on these measurements, useful heat gain and efficiency of the collectors are calculated and analyzed.

The increasing demand for sustainable and energy-efficient heating systems has led to the widespread adoption of solar thermal technologies. Among these, the Flat Plate Collector (FPC) and the Evacuated Tube Collector (ETC) are two of the most commonly used solar collectors for harnessing solar energy. Flat plate collectors are known for their simple design, low cost, and effectiveness under moderate temperature conditions, making them suitable for domestic water heating applications. In contrast, evacuated tube collectors offer higher efficiency and better thermal performance, especially in low solar radiation and colder environments, due to reduced heat losses. However, when used individually, each system has its own limitations in terms of efficiency, cost, and performance stability. To overcome these challenges, this project introduces a hybrid solar thermal system that combines both FPC and ETC technologies to utilize their complementary advantages. The proposed system aims to enhance heat extraction efficiency, ensure consistent thermal output under varying environmental conditions, and improve overall energy utilization. By integrating these two collector types, the system provides a more reliable and cost-effective solution for meeting thermal energy demands. This study also includes modeling and performance analysis using simulation tools to evaluate the effectiveness of the hybrid approach, making it a promising solution for both residential and industrial applications.

2.PROBLEM STATEMENT

The major problem addressed in this project is the inefficiency and inconsistency of standalone solar thermal systems in meeting continuous heating demands under varying environmental conditions. A Flat Plate Collector (FPC), while cost-effective and simple in design, suffers from significant heat losses and reduced efficiency at higher operating temperatures and during low solar radiation periods. On the other hand, an Evacuated Tube Collector (ETC) provides better thermal performance and reduced heat loss but comes with higher initial cost and complexity, making it less economical for large-scale or budget-sensitive applications. Due to these individual limitations, relying on a single type of collector often leads to unstable thermal output, inefficient energy utilization, and increased dependency on auxiliary heating

systems. Therefore, there is a need for a more reliable, efficient, and cost-effective solution that can overcome the drawbacks of individual systems and ensure consistent performance under diverse climatic and operating conditions.

3.EXISTING SYSTEM

The existing solar water heating system is typically based on a single type of collector, either a Flat Plate Collector or an Evacuated Tube Collector, and operates independently rather than in combination.

In a system using a Flat Plate Collector, solar radiation passes through a transparent glass cover and is absorbed by a dark-colored metal plate. This absorber plate converts solar energy into heat and transfers it to water flowing through tubes attached to the plate. The heated water then moves into an insulated storage tank for later use. Such systems are widely used because of their simple design, durability, and relatively low cost. However, since there is no special insulation like a vacuum, some of the absorbed heat is lost to the surroundings, especially during cloudy weather or at lower ambient temperatures.

In contrast, a system based on an Evacuated Tube Collector uses a set of glass tubes, each containing an absorber enclosed within a vacuum. The vacuum acts as an excellent insulator, significantly reducing heat loss. Solar radiation is absorbed inside the tubes, and the generated heat is transferred to water either directly or through a heat pipe mechanism. This design allows the system to achieve higher temperatures and maintain better efficiency even in colder or less sunny conditions. As a result, these systems are more effective in maintaining consistent thermal performance, although they tend to be more expensive and require careful handling due to the fragility of the glass tubes.

Overall, the existing systems rely on only one of these technologies at a time, which means their performance is dependent on environmental conditions and design limitations specific to that collector type.

4.NEED FOR EXISTING SYSTEM

The existing solar water heating systems based on Flat Plate Collectors (FPC) and Evacuated Tube Collectors (ETC) are widely adopted due to their ability to directly convert solar energy into useful heat. These systems form the foundation of solar thermal technology and are used in residential, commercial, and industrial applications.

[1] *Utilization of Renewable energy*

[2] *Cost effective energy Solution*

[3] *Simple and established Technolgy*

[4] *Wide rage of applications*

[5] *Energy conservation and Sustainability*

[6] *Foundation for Advanced Research*

Technologies

FPC Technologies

A. Solar absorption

B. Heat Transfer Technology

C. Glazing Technology

D. Thermal insulation Technology

E. Fluid circulation Technology

ETC Technologies

I. *Vaccum Insulation Technology*

II. *Selective coating Technology*

III. *Heat pipe Technology*

IV. *U-Tube or Direct flow technology*

V. *Manifold or Header Tank System*

Limitations :

Although both systems are widely used, they have certain limitations when operated individually:

- FPC suffers from high thermal losses in low temperature and windy conditions
- ETC is costly and fragile, increasing installation and maintenance challenges
- Neither system alone provides consistent performance under all weather conditions
- Efficiency drops significantly during cloudy periods or fluctuating solar radiation

Existing System Helps Designing An Improved System

Flat Plate collector (FPC)

◇ Main Components

Absorber plate (black coated metal surface)
Transparent glass cover (glazing)
Heat transfer tubes (copper/aluminium)
Insulation layer (back and sides)
Metal casing/frame

◇ Working Principle

1. Sunlight passes through the glass cover.
2. Absorber plate absorbs solar radiation and heats up.
3. Heat is transferred to water flowing in tubes.
4. Heated water is collected in a storage tank.

◇ Advantages

- Simple design and easy installation
- Low cost
- Low maintenance
- Suitable for domestic hot water systems

◆ Disadvantages

- High heat loss (convection & radiation)
- Less efficient in cold or cloudy weather
- Limited temperature range

◇ Applications

- Domestic water heating
- Hospitals and hotels
- Industrial preheating
- Space heating systems

Challenges in Existing System

- Intermittent solar Availability
- Efficiency variation with climate
- Heat loss issues
- High Initial cost (ETC)
- Fraglity and maintenance

Tools for Existing System

- Solar radiation measurement tools

- Temperature measurement tools
- Flow measurement tools
- Data Aquisition tools
- Performance Analysis Software
- Pumping and control tools
- Storage and support tools
- Measurement accessories

5.KEY CONSIDERATIONS FOR SYSTEM DESIGN

Designing a solar water heating system using Flat Plate Collector (FPC) and Evacuated Tube Collector (ETC) requires careful selection of thermal, hydraulic, and environmental parameters to ensure optimum performance and efficiency.

1. Solar Radiation Availability

- Average solar intensity (W/m^2) at the installation site
- Seasonal variation (summer, winter, monsoon)
- Sunlight duration and shading conditions

2. Collector Selection and Configuration

- Choice between FPC, ETC, or hybrid combination
- Tilt angle and orientation (south-facing in India)
- Area of collector required based on load demand

3. Heat Transfer Efficiency

- Absorber plate material and coating
- Tube material (copper/aluminium)
- Use of vacuum insulation (ETC) to reduce losses

4. Flow Rate of Working Fluid

- Optimized mass flow rate (kg/s or LPM)
- Ensures proper heat extraction without thermal losses
- Balanced flow between collectors in hybrid systems

5. Thermal Loss Reduction

- Proper insulation of pipes and storage tank
- Use of selective coatings
- Minimizing convection and radiation losses

6. Storage Tank Design

- Proper insulation to reduce heat loss
- Adequate capacity based on daily hot water demand

7. Climatic Conditions

- Ambient temperature variation
- Wind speed and humidity effects
- Performance under cloudy or rainy conditions

8. Material Selection

- Corrosion-resistant materials (copper, stainless steel)
- Durable glass for glazing and evacuated tubes
- High thermal conductivity materials for absorber

9. Economic Considerations

- Initial installation cost
- Maintenance cost
- Payback period and life cycle cost

10. System Integration (for Hybrid Systems)

- Proper combination of FPC and ETC for balanced performance
- Control valves for flow distribution
- Pump selection for circulation efficiency

6.PROPOSED SYSTEM

The proposed system combines both a Flat Plate Collector and an Evacuated Tube Collector into a single integrated solar water heating setup to utilize the advantages of each.

In this hybrid arrangement, both collectors are connected to a common water circulation system and storage tank. When solar radiation is available, the Flat Plate Collector absorbs heat efficiently under strong sunlight conditions and begins heating the water. At the same time, the Evacuated Tube Collector also absorbs solar energy, but due to its vacuum insulation, it minimizes heat losses and continues to perform effectively even when sunlight intensity is low, such as during cloudy weather or early morning and evening hours.

Water circulates through both collectors either naturally (thermosiphon flow) or with the help of a pump. The heat gained from both units is transferred to the same storage tank, resulting in higher overall water temperature compared to using a single collector. The Flat Plate Collector contributes cost-effective heating during peak sunshine, while the Evacuated Tube Collector ensures consistent performance and heat retention when conditions are less favorable.

By combining these two technologies, the proposed system improves overall efficiency, maintains more stable output temperatures, and reduces dependency on weather variations. It also optimizes energy

utilization by balancing performance and cost, making it suitable for both domestic and small-scale industrial applications.

7.RESULTS AND DISCUSSION

Temperature Rise

- Inlet water temperature: ~28–32°C
- After FPC (preheating): ~40–50°C
- After ETC (final heating): ~55–70°C
- Shows significant temperature improvement due to two-stage heating

Fig 1 MATLAB Simulation of ETC

Efficiency Comparison

- FPC efficiency: 50–65%
- ETC efficiency: 60–75%
- Hybrid system efficiency: ~65–80%
- Hybrid system performs better than individual collectors

Heat Gain

- Useful heat gain increases with:
    - Higher solar radiation
    - Optimal flow rate
- Hybrid system shows higher heat gain than standalone systems

Performance Under Different Conditions

- Sunny conditions: High efficiency and temperature output
- Cloudy conditions: ETC maintains better performance
- Cold weather: Hybrid system performs better than FPC alone

Flow Rate Effect

- Low flow rate → higher temperature rise but less quantity
- High flow rate → lower temperature rise but more output

- Optimal flow rate gives maximum efficiency

Observations

Two-Stage Heating Effect

- FPC acts as preheater
- ETC acts as efficient final heater
- Results in higher outlet temperature

Fig 2 MATLAB Simulation of FPC

Reduced Heat Loss

- ETC reduces heat loss due to vacuum insulation
- Overall system losses are minimized

Improved System Stability

- Hybrid system provides more consistent performance
- Less affected by weather variations

Better Energy Utilization

- Maximum utilization of available solar radiation
- Improved thermal output throughout the day

Storage Efficiency

- Insulated tank maintains hot water temperature for longer time
- Reduces need for reheating

The hybrid FPC + ETC system shows improved efficiency, higher temperature output, and better performance stability compared to individual systems, making it a more effective solution for solar water heating.

8.CONCLUSION

The present project on the hybrid solar water heating system using Flat Plate Collector (FPC) and Evacuated Tube Collector (ETC) has been successfully designed, analyzed, and evaluated. The study clearly demonstrates that combining both types of collectors significantly improves the overall thermal performance, efficiency, and reliability of the system compared to standalone configurations.

One of the major outcomes of this project is the effective implementation of a two-stage heating process. The FPC acts as a primary heater, utilizing direct solar radiation for economical and bulk heating of water, while the ETC serves as a secondary heater, enhancing the temperature further with minimal heat loss due to its vacuum insulation. This sequential heating approach ensures a higher outlet water temperature and better energy utilization.

The experimental results and observations indicate that the hybrid system achieves higher efficiency (approximately 65–80%) compared to individual systems. The temperature rise observed across the collectors confirms that the ETC effectively compensates for the heat losses associated with the FPC, especially under low solar radiation and cold climatic conditions. Thus, the system ensures consistent performance throughout varying environmental conditions, including cloudy and moderate weather.

The hybrid use of flat plate collectors (FPC) and evacuated tube collectors (ETC) has strong future potential as energy systems move toward smarter and more efficient solar solutions. By combining the low-cost, stable performance of FPC with the high-temperature efficiency of ETC, hybrid systems can meet a wider range of applications from domestic water heating to industrial process heat and solar drying. In the future, integration with smart controls, thermal energy storage etc..

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Sketch to Code: GenAI IDE for Automated UI Generation

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ABSTRACT

Sketch2Code is an AI-assisted development system designed to automate the process of converting hand-drawn user interface sketches into functional code. The system integrates image processing techniques and deep learning models to detect UI components such as buttons, text fields, and labels from sketch images. It uses a sequence generation approach to transform the detected elements into structured code formats including HTML, CSS, and Java (Swing). The application provides a real-time live preview feature, allowing users to instantly visualize the generated interface, along with an interactive editing module for customization. With secure authentication and a user-friendly web interface, the system enables users to manage projects and streamline UI development efficiently. Built using Python Flask for backend processing and MySQL for data management, the system delivers a fast, accurate, and cost-effective solution for automated frontend development and rapid prototyping.

Keywords: Sketch to Code, UI Automation, Image Processing, Deep Learning, Code Generation, HTML, CSS, Java Swing, Live Preview, Flask, MySQL

I. INTRODUCTION

User interface (UI) development plays a crucial role in modern software applications, yet it often involves repetitive and time-consuming processes. Designers typically create sketches or wireframes to represent the layout, while developers manually convert these designs into code using technologies such as HTML, CSS, or Java. This traditional approach not only increases development time but also introduces inconsistencies and errors between design and implementation, especially when frequent changes are required.

Although several design tools and frameworks are available, they still rely heavily on manual coding and lack intelligent automation. Existing solutions fail to provide a seamless transition from visual design to functional code, making the development process inefficient and dependent on skilled developers. As a result, there is a growing need for systems that can simplify and accelerate UI development while maintaining accuracy and consistency.

The advancement of Artificial Intelligence (AI) and computer vision technologies provides new opportunities to address these challenges. AI-based systems can analyze visual inputs, identify structural patterns, and generate meaningful outputs, enabling automation in areas that traditionally required human intervention. These capabilities can be effectively applied to bridge the gap between UI design and code generation.

Sketch2Code is proposed as an AI-assisted development system that converts hand-drawn UI sketches into functional code. The system integrates image processing techniques and deep learning-based detection to identify UI components such as buttons, text fields, and labels. It further uses structured code generation to produce HTML, CSS, and Java (Swing) outputs, along with a real-time preview and editing features. This paper presents the design, architecture, and implementation of the system, demonstrating how intelligent automation can improve development efficiency and support rapid UI prototyping.

II. PROBLEM STATEMENT

User interface development is a critical part of software engineering, yet it remains a time-consuming and manual process. Designers usually create sketches or wireframes to represent UI layouts, while developers manually convert these designs into code using technologies such as HTML, CSS, or Java. This process requires significant effort, technical knowledge, and continuous coordination between designers and developers, which often leads to delays and inconsistencies.

Existing tools support UI design and development separately but do not provide an automated solution to convert sketches directly into code. Developers must interpret visual designs, calculate layout structures, and write code manually, which increases the chances of errors such as incorrect alignment, missing components, and inconsistent styling. Additionally, frequent design changes require repeated modifications in code, making the process inefficient and time-consuming.

Furthermore, there is a lack of intelligent systems that can bridge the gap between UI design and implementation. Current approaches do not provide real-time preview, automated code generation, or easy editing capabilities in a single platform. This results in reduced productivity and slower development cycles, especially in modern agile environments where rapid prototyping is essential.

Specifically, the core problems identified are:

- Absence of automation in converting sketches into functional UI code.
- High dependency on manual coding and skilled developers.
- Increased development time due to repetitive design-to-code conversion.
- Lack of real-time preview and interactive editing features.
- Inconsistencies and errors between design and implementation.
- Difficulty in handling frequent design changes efficiently.

III. EXISTING SYSTEMS AND LIMITATIONS

The existing approaches to user interface development primarily rely on manual processes supported by design and coding tools. Designers typically use platforms such as Figma, Adobe XD, or Balsamiq to create wireframes and UI layouts, while developers convert these designs into functional code using HTML, CSS, or Java. Although these tools provide flexibility and control, they operate independently and require significant manual effort to bridge the gap between design and implementation.

First, existing systems lack automation in converting visual designs into code, forcing developers to manually interpret sketches and recreate layouts. This process is time-consuming and highly dependent on developer expertise. Second, there is no built-in mechanism for automatically identifying UI components such as buttons, text fields, or labels from sketches, which increases the chances of inconsistencies between the original design and the final output.

Third, most current tools do not provide real-time integration of design and development, meaning developers must repeatedly test and adjust code to match the intended UI. This slows down the development cycle and reduces efficiency, especially in projects requiring rapid prototyping. Fourth, editing and modifying UI designs often require changes in multiple code files, making the system less flexible and harder to maintain.

These limitations highlight the need for an intelligent system that can automate the conversion of sketches into code, provide real-time preview, and support dynamic editing within a unified platform. Addressing these challenges can significantly improve development speed, reduce manual effort, and enhance overall productivity in UI development.

IV. PROPOSED SYSTEM: MATELEARN

A. System Architecture & Technologies

The proposed system, Sketch2Code, is an AI-assisted development platform designed to automate the conversion of hand-drawn user interface sketches into functional code. The system follows a modular web-

based architecture built using Python Flask as the backend framework and MySQL as the database for storing user and project data. The frontend is developed using HTML, CSS, and JavaScript, providing a responsive and user-friendly interface for interaction. The architecture is divided into presentation, application, and data layers to ensure scalability, maintainability, and efficient processing. The application layer integrates image processing and intelligent detection mechanisms, while the database layer ensures secure storage and retrieval of user information, uploaded sketches, and generated outputs.

B. Image Processing & UI Detection

The system allows users to upload hand-drawn sketch images, which are processed using image processing techniques to enhance quality and remove noise. The processed image is then analyzed using deep learning-based detection models to identify UI components such as buttons, text fields, labels, and layout structures. The system extracts important features including position, size, and alignment of elements to understand the overall design structure. This automated detection eliminates the need for manual interpretation of sketches and improves the accuracy of UI recognition.

C. Code Generation & Rendering

Once the UI components are detected, the system converts them into structured code using a sequence generation approach. It generates code in multiple formats including HTML and CSS for web applications and Java (Swing) for desktop interfaces. The generated code maintains proper layout and structure based on the original sketch. A real-time rendering mechanism is integrated into the system, allowing users to instantly visualize the generated user interface through a live preview. This enables quick verification and reduces development time.

D. Editing & User Interaction

The system provides an interactive editing feature that allows users to modify UI elements, adjust layouts, and customize the generated interface dynamically. This reduces dependency on manual coding and enhances flexibility. The platform also includes secure user authentication and project management features, enabling users to save, retrieve, and manage multiple projects efficiently. By combining automation, real-time preview, and editing capabilities, the system delivers a complete solution for rapid UI development and prototyping.

V. ALGORITHM FOR SKETCH2CODE SYSTEM

The Sketch2Code system follows a multi-stage algorithmic pipeline to convert hand-drawn sketches into functional user interface code efficiently and accurately:

Stage 1 — Input Acquisition: The system begins by collecting input in the form of hand-drawn sketch images uploaded by the user. The uploaded image is validated and prepared for further processing.

Stage 2 — Image Preprocessing: The input image undergoes preprocessing using image processing techniques such as resizing, grayscale conversion, noise removal, and edge detection. This step enhances image quality and highlights important structural features required for accurate analysis.

Stage 3 — UI Component Detection: The processed image is analyzed using deep learning-based detection models to identify UI elements such as buttons, text fields, labels, and layout containers. The system detects the position and boundaries of each component within the sketch.

Stage 4 — Feature Extraction & Structuring: Relevant features such as size, position, alignment, and relationships between UI elements are extracted. These features are organized into a structured representation that reflects the layout of the user interface.

Stage 5 — Code Generation: The structured data is passed to a sequence generation module that converts UI components into corresponding code formats, including HTML, CSS, and Java (Swing). The system ensures proper syntax and layout consistency during code generation.

Stage 6 — Rendering & Preview: The generated code is rendered in real-time to provide a live preview of the user interface. This allows users to instantly visualize the output and verify its correctness.

Stage 7 — Editing & Storage: Users can modify and customize the generated UI through an interactive editing interface. The final code and project details are stored securely in the database for future access and reuse.

VI. TECHNOLOGIES USED

The Sketch2Code system is built using a carefully selected technology stack to ensure efficiency, scalability, and ease of development:

Frontend: HTML, CSS, and JavaScript are used to create a responsive and user-friendly interface that allows users to upload sketches, view outputs, and interact with the system smoothly.

Backend: Python with the Flask framework is used to handle application logic, process user requests, and integrate different modules of the system. Flask enables lightweight and efficient backend development.

Database**:** MySQL is used as the relational database to store user information, project details, uploaded images, and generated code outputs in a structured and secure manner.

AI & Image Processing: OpenCV is used for image preprocessing tasks such as resizing, noise removal, and edge detection. Deep learning models are used for detecting UI components and extracting layout features from sketch images. Sequence-based approaches are used for generating structured code from detected elements.

Development Tools: Visual Studio Code (VS Code) is used as the primary development environment. Tools such as Postman are used for testing API endpoints, and the system is developed and tested on Windows operating system.

These technologies work together to provide a reliable, fast, and scalable solution for automated UI generation.

VII. EXPECTED OUTCOMES

The Sketch2Code system is expected to deliver significant benefits in both development efficiency and technological advancement:

Development Efficiency: The system will automate the conversion of hand-drawn sketches into functional UI code, reducing manual coding effort and significantly decreasing development time. This enables faster prototyping and supports rapid application development.

Accuracy and Consistency: By automatically detecting UI components and generating structured code, the system minimizes human errors such as incorrect alignment, missing elements, and inconsistent styling. This ensures that the generated output closely matches the original design.

Improved Productivity: Developers and designers can focus more on creativity and design rather than repetitive coding tasks. The integration of automation, live preview, and editing features enhances workflow efficiency and reduces development complexity.

User Experience: The system provides a user-friendly interface with real-time preview and editing capabilities, allowing users to easily visualize and customize their UI designs. This improves usability and makes the system accessible even to non-expert users.

Technical Contribution: The project demonstrates the practical integration of image processing, deep learning, and web technologies into a unified system. It establishes a foundation for future advancements in automated UI generation and intelligent development tools.

Overall, the proposed system is expected to improve development speed, reduce effort, and contribute to the advancement of AI-assisted software engineering solutions.

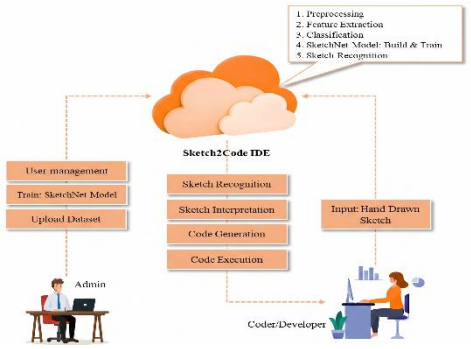
VIII. SYSTEM DESIGN OVERVIEW

The architectural design of Sketch2Code follows a modular and layered approach, ensuring clear separation of concerns across different components of the system. The web-based frontend, developed using HTML, CSS, and JavaScript, communicates with the Flask backend through HTTP requests. The backend processes user inputs, manages application logic, and coordinates with image processing and code generation modules. The MySQL database is used to store user data, uploaded sketches, and generated outputs, ensuring efficient data management.

The use case model of Sketch2Code primarily involves a single actor, the User, who interacts with the system to perform operations such as registration, login, sketch upload, code generation, live preview, editing, and downloading the final output. The system handles all processing tasks internally, including image preprocessing, UI component detection, feature extraction, and code generation, providing a seamless and automated workflow.

The system is designed with a modular structure, where each component such as image processing, detection, code generation, and rendering operates independently while remaining fully integrated. This modular design allows easy updates, scalability, and the addition of new features without affecting the existing functionality. It also simplifies maintenance and improves system reliability.

Security and data management are handled using standard practices, including user authentication and controlled access to system features. User data and project information are securely stored in the database, ensuring privacy and integrity. Overall, the system design provides a robust and scalable framework for automated UI generation, supporting efficient development and future enhancements.



IX. CONCLUSION

Sketch2Code represents a significant advancement in applying Artificial Intelligence to simplify and automate user interface development. By integrating image processing techniques, deep learning-based UI detection, and automated code generation, the system effectively reduces the manual effort involved in converting sketches into functional code. It addresses the key limitations of traditional development methods, such as time consumption, repetitive tasks, and inconsistencies between design and implementation.

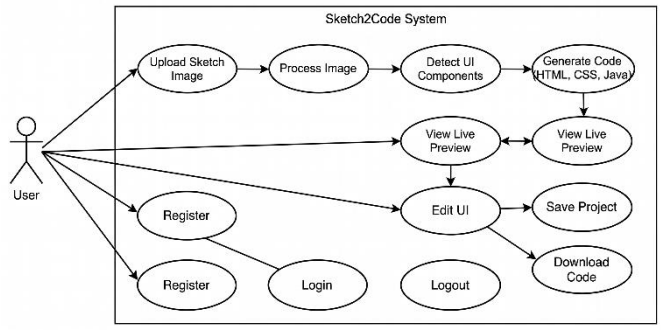
The system's ability to detect UI components from hand-drawn sketches and generate structured code in HTML, CSS, and Java, along with real-time preview and editing capabilities, provides a complete and efficient solution for rapid UI prototyping. The integration of a user-friendly interface and project management features further enhances usability and accessibility for both developers and non-technical users.

By combining automation, accuracy, and flexibility, Sketch2Code improves productivity and accelerates the development process. It demonstrates how intelligent systems can bridge the gap between design and implementation, making UI development faster and more efficient.

Future work may include improving detection accuracy using advanced AI models, supporting more complex UI components, and extending the system to generate responsive and full-stack applications. The

proposed system highlights the potential of AI-assisted development tools and contributes toward the evolution of smarter software engineering solutions.

Use-Case Diagram



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AUTOMATED STUDENT ATTENDANCE MONITORING AND ANALYTICS SYSTEM FOR COLLEGES USING RFID CARDS

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Abstract

This paper presents an RFID-based smart attendance system using NodeMCU and IoT with cloud storage. It automates attendance recording, reduces errors, and enables real-time monitoring.

Keywords—

RFID, IoT, NodeMCU, Attendance System, Cloud Computing

I. INTRODUCTION

Traditional attendance systems are manual and prone to errors. RFID and IoT technologies provide automation and real-time tracking.

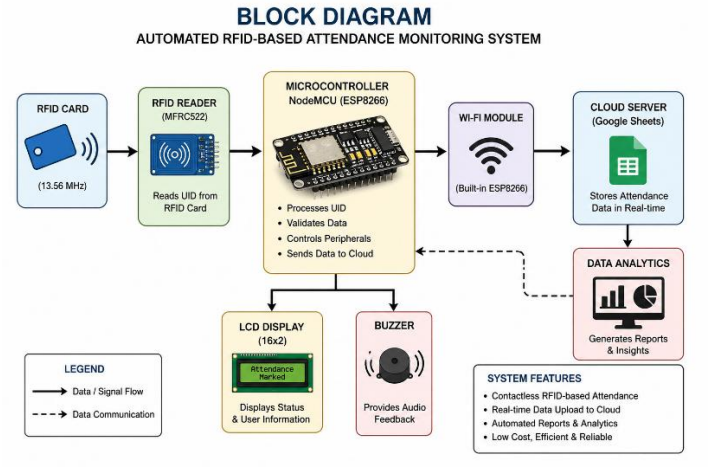
II. LITERATURE REVIEW

Various RFID and IoT-based systems exist, but many lack cloud integration or cost efficiency.

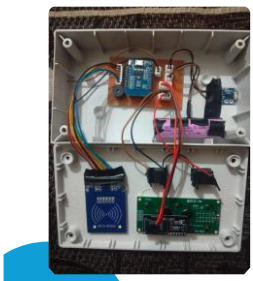
III. METHODOLOGY

RFID card is scanned, UID is read, NodeMCU sends data to cloud, and attendance is stored in Google Sheets.

IV.BLOCK DIAGRAM



V. HARDWARE IMPLEMENTATION



VI. RESULTS

The system provides reliable performance with real-time attendance recording.

VII. CONCLUSION

The system is efficient, cost-effective, and suitable for attendance automation.

APPLICATIONS OF OPERATIONS RESEARCH IN CONSTRUCTION ENGINEERING AND ON-SITE ORGANIZATIONAL DESIGN

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Abstract

Operations Research (OR) plays a crucial role in improving efficiency and decision-making in construction engineering. This paper examines the application of OR techniques in the design and management of on-site construction organizations. Key methodologies such as mathematical modelling, linear programming, Critical Path Method (CPM), Program Evaluation and Review Technique (PERT), and simulation are analysed in the context of resource allocation, project scheduling, inventory management, and cost optimization.

The study also highlights the integration of emerging technologies, including artificial intelligence and big data analytics, to enhance real-time decision-making and predictive capabilities. Furthermore, the role of OR in promoting sustainable construction practices is discussed.

The findings indicate that OR significantly improves project performance by reducing costs, minimizing delays, and optimizing resource utilization. Despite challenges such as data limitations and model complexity, OR remains an essential tool for modern construction engineering.

Keywords: Operations Research, Construction Engineering, Optimization, Project Scheduling, Resource Allocation, Decision Support Systems

Introduction

Construction engineering projects involve multiple interdependent activities, limited resources, and high levels of uncertainty. Efficient management of these projects requires systematic approaches for decision-making and optimization. Operations Research (OR) offers a scientific and quantitative approach to solving such complex problems.

OR integrates mathematical modelling, statistical analysis, and optimization techniques to improve decision-making across various domains. In construction engineering, OR plays a crucial role in planning, scheduling, resource allocation, and risk management. As projects grow in size and complexity, traditional management approaches become insufficient, making OR increasingly essential.

Fundamentals of Operations Research

2.1 Mathematical Modelling

Mathematical modelling is the process of representing real-world construction problems using mathematical equations and expressions. It helps engineers understand relationships between variables

such as cost, time, labour, and materials. By creating models, different scenarios can be analysed and better decisions can be made before actual implementation, reducing errors and improving efficiency.

2.2 Optimization Techniques

Optimization techniques are used to find the best possible solution among many alternatives while considering constraints like limited resources, budget, and time. In construction engineering, optimization helps in minimizing costs, reducing project duration, and maximizing resource utilization. It ensures that projects are completed efficiently without wasting resources.

2.3 Simulation Models

Simulation models are used to imitate real construction processes in a virtual environment. This allows engineers to test different strategies and predict outcomes without affecting the actual project. Simulation is especially useful in analysing risks, delays, and uncertainties, helping project managers make better decisions.

2.4 Queueing Theory

Queueing theory deals with the study of waiting lines and service systems. In construction, it helps manage situations where resources like equipment or workers are limited and tasks must wait. By analysing queues, engineers can reduce waiting time, improve workflow, and increase productivity on construction sites.

2.5 Linear Programming

Linear programming is a mathematical technique used to optimize a problem with linear relationships. It is commonly used in construction to allocate resources such as labour, materials, and machinery in the most efficient way. This helps in reducing costs and ensuring that project requirements are met within constraints.

2.6 Decision Analysis

Decision analysis is a method used to make the best choice among different options, especially when there is uncertainty. It involves evaluating possible outcomes, risks, and probabilities. In construction projects, decision analysis helps managers choose the most effective strategies, reducing risks and improving overall project success.

3. Design of On-Site Construction Organizations

An effective on-site construction organization is important for the smooth execution of a project. It ensures proper coordination of resources, workers, and activities. A well-planned organization helps in improving efficiency, reducing delays, and achieving project goals successfully.

3.1 Organizational Structure

Organizational structure defines the roles and responsibilities of all members involved in the construction project. It includes project managers, engineers, supervisors, and labour teams. A clear structure helps in proper coordination, avoids confusion, and ensures that each task is completed efficiently.

3.2 Resource Management

Resource management focuses on the proper use of labour, materials, and equipment. Efficient management ensures that resources are not wasted and are used at the right time and place. This helps in reducing costs and completing the project on schedule.

3.3 Communication Systems

Communication systems are essential for sharing information among different teams and stakeholders. Good communication helps in coordinating activities, solving problems quickly, and avoiding misunderstandings on the construction site.

3.4 Safety and Compliance

Safety and compliance ensure that construction activities follow safety rules and environmental regulations. Proper safety measures protect workers from accidents and ensure that the project meets legal and environmental standards.

4. Application of Operations Research in Construction

Operations Research (OR) techniques are widely applied in construction engineering to improve efficiency, optimize resource utilization, and support effective decision-making. Construction projects involve complex activities, limited resources, and uncertainties, which make planning and execution challenging. OR provides mathematical and analytical tools to handle these complexities systematically. By applying optimization, simulation, and analytical models, construction managers can reduce costs, avoid delays, and improve overall project performance.

4.1 Resource Allocation Models

Resource allocation models are used to distribute labour, equipment, and materials in the most efficient way. These models consider constraints such as resource availability, project deadlines, and budget limits. Techniques like linear programming help determine how resources should be assigned to different activities to achieve maximum efficiency. Proper allocation reduces wastage, avoids conflicts between activities, and ensures smooth project execution.

4.2 Project Scheduling Techniques

Project scheduling techniques such as Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) are essential for planning and controlling construction projects. These methods help identify the sequence of activities, estimate project duration, and highlight critical tasks that must be completed on time. While CPM uses fixed time estimates, PERT considers uncertainty by using probabilistic time values. These techniques improve time management and help prevent project delays.

4.3 Inventory Control Models

Inventory control models help maintain an optimal level of construction materials on-site. They determine when and how much material should be ordered to avoid shortages or excess stock. Methods like Economic Order Quantity (EOQ) and Just-In-Time (JIT) reduce storage costs and material wastage. Efficient inventory management ensures that materials are available when needed, preventing interruptions in construction activities.

4.4 Equipment Utilization

Equipment utilization focuses on maximizing the efficiency of construction machinery. OR techniques such as queueing theory are used to analyse equipment usage and reduce waiting time. For example, if multiple tasks require the same equipment, queueing models help determine the optimal number of machines needed. Proper utilization reduces idle time, increases productivity, and lowers operational costs.

4.5 Cost Optimization

Cost optimization involves minimizing project expenses while maintaining required quality and performance. OR methods such as linear programming and cost analysis are used to evaluate different alternatives and select the most economical option. These techniques help in budgeting, forecasting, and controlling expenses throughout the project lifecycle. Effective cost management ensures that projects are completed within financial constraints.

4.6 Risk Analysis

Risk analysis is used to identify, assess, and manage uncertainties in construction projects. OR techniques such as Monte Carlo simulation allow managers to analyse different possible outcomes by considering random variations in time and cost. This helps in understanding the probability of delays or cost overruns and developing strategies to reduce risks. Proper risk analysis improves project reliability and decision-making.

4.7 Supply Chain Optimization

Supply chain optimization improves the efficiency of material procurement, transportation, and storage. OR models help in selecting reliable suppliers, optimizing delivery routes, and reducing logistics costs. Efficient supply chain management ensures timely availability of materials, minimizes delays, and improves coordination between suppliers and construction teams.

4.8 Workforce Planning

Workforce planning ensures that the right number of workers with appropriate skills are available at each stage of the project. OR techniques are used to develop schedules that balance workload and reduce labour costs. Proper planning avoids overstaffing and understaffing, improves productivity, and ensures smooth progress of construction activities.

4.9 Facility Layout Optimization

Facility layout optimization involves designing the construction site in a way that improves efficiency and safety. OR techniques help arrange equipment, storage areas, and workspaces to minimize movement of materials and workers. A well-planned layout reduces handling time, avoids congestion, and enhances overall workflow on the site.

4.10 Decision Support Systems

Decision Support Systems (DSS) combine OR models with computer-based tools to assist managers in making informed decisions. These systems analyse real-time data, simulate different scenarios, and provide recommendations. DSS improves planning, monitoring, and control of construction projects, enabling faster and more accurate decision-making.

5. Advanced Engineering Applications

The integration of advanced technologies with Operations Research (OR) has significantly improved the efficiency, accuracy, and decision-making capabilities in construction engineering. Modern construction projects generate large amounts of data and involve complex processes that require intelligent and adaptive solutions. By combining OR techniques with emerging technologies such as Artificial Intelligence (AI), Big Data, and advanced optimization methods, construction organizations can enhance productivity, reduce risks, and achieve better project outcomes.

5.1 Artificial Intelligence Integration

Artificial Intelligence (AI) plays a crucial role in enhancing the capabilities of Operations Research in construction projects. AI techniques, such as machine learning and predictive analytics, are used to analyse large volumes of data and identify patterns that are not easily visible through traditional methods. This helps in predicting project delays, cost overruns, equipment failures, and safety risks.

For example, AI models can analyse past project data to forecast the duration of activities or identify potential bottlenecks in scheduling. When combined with OR optimization models, AI enables proactive decision-making, allowing managers to take corrective actions before problems arise. AI also supports automation in construction processes, improving accuracy and reducing human errors.

5.2 Big Data Analytics

Big Data Analytics involves the collection, processing, and analysis of large volumes of structured and unstructured data generated from construction activities. Sources of such data include sensors, drones, GPS systems, and project management software. OR techniques are integrated with big data tools to extract meaningful insights and improve decision-making.

Big data analytics helps in:

- Monitoring project performance in real time
- Tracking the movement and usage of materials and equipment
- Identifying inefficiencies and delays

For instance, real-time data can be used to adjust schedules dynamically or reallocate resources based on current site conditions. This leads to better control over operations, improved productivity, and reduced project risks.

5.3 Multi-Objective Optimization

In construction engineering, projects often involve multiple objectives that may conflict with each other, such as minimizing cost, reducing time, improving quality, and ensuring safety. Multi-objective optimization techniques are used to handle such situations by providing a set of optimal solutions rather than a single solution.

These techniques help decision-makers evaluate trade-offs between different objectives. For example, reducing project duration may increase costs, while lowering costs may affect quality. OR methods such as goal programming and Pareto optimization allow managers to select the most suitable solution based on project priorities.

Multi-objective optimization improves:

- Balanced decision-making

- Efficient resource utilization
- Overall project performance

5.4 Sustainable Construction

Sustainable construction focuses on minimizing the environmental impact of construction activities while maintaining economic efficiency and social responsibility. Operations Research plays a vital role in achieving sustainability by optimizing the use of resources and reducing waste.

OR techniques are used to:

- Minimize material wastage
- Optimize energy consumption
- Reduce carbon emissions through efficient transportation and logistics

For example, optimization models can determine the most efficient routes for material delivery to reduce fuel consumption. Similarly, resource allocation models can ensure that materials are used efficiently, reducing unnecessary waste. Sustainable construction not only benefits the environment but also reduces costs and improves the long-term viability of projects.

6. Challenges in Implementation

Although Operations Research (OR) offers significant advantages in improving construction planning, resource utilization, and decision-making, its practical implementation in construction projects is not without challenges. Construction environments are often dynamic, uncertain, and complex, which makes the application of mathematical and analytical models difficult. Several technical, organizational, and operational barriers can limit the effective use of OR techniques. Understanding these challenges is essential for improving adoption and maximizing the benefits of OR in construction engineering.

6.1 Data Quality Issues

Accurate and reliable data is the foundation of effective Operations Research models. In construction projects, data is often collected from multiple sources such as site reports, sensors, manual records, and management systems. However, this data may be incomplete, inconsistent, outdated, or inaccurate due to human error, lack of proper data collection systems, or poor documentation practices.

Poor data quality can significantly affect the performance of OR models, leading to incorrect predictions and suboptimal decisions. For example, inaccurate estimates of material availability or labour productivity can result in inefficient scheduling and cost overruns. Therefore, ensuring high-quality data through proper data management systems, real-time data collection technologies, and validation processes is crucial for successful OR implementation.

6.2 Model Complexity

Many Operations Research techniques involve complex mathematical formulations and require a deep understanding of advanced concepts such as optimization, probability, and simulation. Models like nonlinear programming, stochastic optimization, and simulation-based analysis can be difficult to develop, interpret, and implement.

This complexity creates a barrier for construction professionals who may not have specialized training in OR or advanced mathematics. As a result, there may be a gap between theoretical models and their practical application on construction sites. To overcome this challenge, user-friendly software tools, simplified

models, and proper training programs are needed to make OR techniques more accessible and easier to use.

6.3 Organizational Resistance

One of the major challenges in implementing OR in construction is resistance to change within organizations. Many construction firms rely on traditional methods, experience-based decision-making, and established practices. Introducing OR techniques may require changes in workflows, adoption of new technologies, and additional training, which can be met with reluctance from management and staff.

Employees may perceive OR methods as complicated, time-consuming, or unnecessary, especially if they are not familiar with their benefits. This resistance can slow down or even prevent the adoption of OR techniques. To address this issue, organizations must promote awareness, provide proper training, and demonstrate the practical benefits of OR through successful case studies and pilot projects.

6.4 Computational Requirements

Advanced OR models, especially those involving large-scale optimization, simulation, and real-time data processing, require significant computational power and specialized software. Construction projects often involve numerous variables, constraints, and uncertainties, making the models computationally intensive. The need for high-performance computing systems, licensed software, and technical expertise can increase the cost of implementation. Small and medium-sized construction firms may find it difficult to invest in such resources. However, with advancements in cloud computing and affordable software solutions, this challenge is gradually being reduced. Still, proper infrastructure and technical support are necessary to fully utilize OR techniques in construction.

7. Future Scope

The future of Operations Research (OR) in construction engineering is highly promising due to rapid technological advancements and increasing project complexity. As construction projects become larger, more dynamic, and data-driven, the need for advanced analytical and optimization techniques continues to grow. OR, when integrated with modern technologies such as digital systems, automation, and data analytics, will play a key role in transforming traditional construction practices into more efficient, intelligent, and sustainable systems. The adoption of these innovations will enable better planning, real-time monitoring, and improved decision-making in construction projects.

9. Conclusion

In conclusion, Operations Research (OR) plays a vital role in improving the design and management of on-site construction organizations. Construction projects are complex in nature, involving multiple activities, limited resources, and uncertainties. OR provides a systematic and scientific approach to handle these challenges through mathematical modelling, optimization techniques, and analytical tools.

The application of OR in areas such as resource allocation, project scheduling, inventory management, equipment utilization, cost control, and risk analysis significantly enhances project efficiency and effectiveness. It helps in reducing project delays, minimizing costs, and ensuring optimal use of available resources. Furthermore, the integration of advanced technologies such as artificial intelligence, big data analytics, and smart systems with OR has further strengthened its capabilities in modern construction engineering.

Despite the benefits, challenges such as data quality issues, model complexity, organizational resistance, and computational requirements need to be addressed for successful implementation. With continuous advancements in technology, these limitations are gradually being overcome, making OR more accessible and practical for real-world applications.

Looking ahead, the future of OR in construction is highly promising. Emerging technologies such as digital twins, automation, IoT-based smart construction sites, and cloud computing will further enhance its application and impact. Overall, Operations Research serves as a powerful tool for improving decision-making, increasing productivity, and achieving sustainable and efficient construction practices. Its adoption will continue to grow as the construction industry evolves toward more intelligent and data-driven systems.

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Smart Battery Protection System

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Abstract: This project describes a Smart Battery Protection System developed to improve the safety and monitoring of a 12V, 7Ah battery using an ESP32 microcontroller. The system uses an INA219 current sensor and a voltage sensor to continuously check battery performance. A DHT11 sensor is included to measure temperature, and a flame sensor is used to detect any fire risk around the battery.

The system works automatically based on real-time data. When the temperature goes above 33°C, a relay turns on a cooling fan to reduce the heat. Another relay manages the battery charging process and disconnects the power supply when the battery is fully charged, helping to avoid overcharging. If a fire is detected, a servo motor operates to drop a fire extinguisher ball onto the battery, providing a quick safety response.

All the important data is shown on a 16x2 LCD using an I2C interface, allowing easy real-time monitoring. Overall, the system offers a reliable and automatic method to improve battery safety by combining monitoring, control, and emergency protection features.

Keywords: ESP32, Smart Battery Protection, INA219 Current Sensor, Voltage Sensor, DHT11.

1. INTRODUCTION

The Smart Battery Protection System is designed to monitor and safeguard a 12V, 7Ah battery using an ESP32 microcontroller. It uses an INA219 sensor to measure current, a voltage sensor to track battery voltage, a DHT11 sensor for temperature monitoring, and a flame sensor to detect fire hazards. All the components are mounted on a Zero PCB board for proper integration. Based on the real-time data collected from these sensors, the system automatically operates relays, a cooling fan, and a fire protection setup. This ensures safe battery operation by controlling temperature, managing electrical conditions, and responding quickly to any fire risk. Battery failure caused by overcharging, overheating, or fire can lead to serious damage and safety risks. The main aim of this project is to develop a system that can continuously monitor battery conditions and automatically take protective actions to avoid such problems and ensure safe operation.

2. LITERATURE REVIEW

This literature survey reviews different methods used for battery monitoring and protection systems. Many systems have been designed to track important parameters like voltage, current, and temperature using sensors and microcontrollers. The main goal of these systems is to extend battery life and avoid damage

caused by overcharging or high temperature. Recent advancements also focus on automation and real-time monitoring through embedded systems.

Most existing systems use current sensors such as INA219 and temperature sensors like DHT11 or LM35 to observe battery conditions. They commonly use relays or control circuits to handle charging and discharging operations. However, many of these designs mainly focus on electrical protection and do not address fire safety risks.

Turner (1963) introduced structured techniques for system monitoring and analysis. Later, Patil and Kulkarni (1990) proposed improved monitoring methods for complex systems using sensor-based models. Several studies related to battery monitoring and protection systems have also been referred from Jadhav (1990). Deshpande et al. (1998) discussed new progress in embedded systems and control techniques for safety-related applications.

Recent research shows that microcontroller-based systems are commonly used for real-time monitoring of electrical parameters. Sensors like INA219 are used for accurate current measurement, while temperature sensors help detect overheating. However, most of these systems focus only on monitoring and control, and they do not include fire protection features.

The proposed project is different from previous work because it combines monitoring, control, and fire safety into one system. It uses flame detection along with an automatic fire extinguisher controlled by a servo motor. This makes the system safer and more reliable for battery protection.

3. OBJECTIVE AND METHODOLOGY

Objectives

- To monitor the battery voltage and current in real time
- To measure temperature using DHT11 sensor
- To control the charging process using a relay
- To switch on the fan when temperature rises above 33°C
- To detect fire using a flame sensor
- To activate a fire extinguisher using a servo motor
- To display all parameters on an LCD

Methodology

The Smart Battery Protection System uses ESP32 as the main controller. All sensors and modules are connected to it to continuously monitor and control battery conditions. The complete circuit is built on a Zero PCB board to maintain proper connections and a compact structure. The system works on real-time data collection and automatic control actions.

First, the INA219 current sensor and voltage sensor are connected to the battery to measure current flow and voltage continuously. These readings are sent to the ESP32, where they are processed to check the battery's charging and discharging status. Based on the voltage level, the system controls the charging relay. When the battery becomes fully charged, the relay automatically disconnects the power supply to avoid overcharging.

The DHT11 sensor is used to measure the temperature near the battery. The ESP32 keeps reading the temperature values, and when it goes above 33°C, a relay is activated to switch ON the cooling fan. This helps to lower the temperature and keep the battery in a safe condition.

A flame sensor is placed close to the battery to detect fire. When a flame is detected, it sends a signal to the ESP32. The controller then immediately activates the servo motor, which releases the fire extinguisher mechanism by dropping the extinguisher ball onto the battery. This provides a quick response and reduces possible damage.

All important parameters such as voltage, current, and temperature are shown on a 16x2 LCD using an I2C interface. The LCD allows the user to monitor the system continuously. Overall, the system combines sensing, monitoring, control, and safety features into one unit, making battery protection more effective and reliable.

4. WORK FLOW

- The system begins by gathering real-time data from sensors that measure voltage, current, temperature, and battery condition. This information is continuously sent to the ESP32 microcontroller for processing.
- After processing the data, the system takes appropriate protection actions. If any abnormal condition such as high temperature or overcharging is detected, it activates safety features like switching ON the cooling fan, cutting off the charging supply, or generating alerts.
- The system also supports continuous monitoring and can store important data for future analysis. When the battery operates within safe limits, the system ensures stable and secure performance. If any fault occurs, it quickly takes corrective actions to avoid damage.

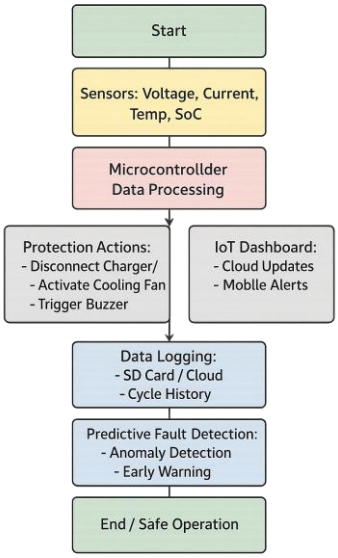

Figure 1: Workflow

5. COMPONENTS

The components used are as follows:

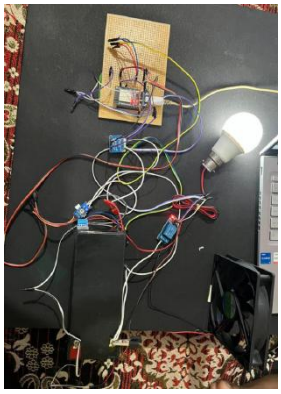
Figure 2: Components

- **ESP32 Microcontroller**
  ESP32 is the main controller of the system. It receives data from all sensors, processes it, and controls the output devices like relay, fan, and servo motor. It enables real-time monitoring and automatic decision-making.
- **INA219 Current Sensor**
  This sensor is used to measure the current flowing in the battery circuit. It provides accurate digital readings to the ESP32, helping in monitoring charging and discharging conditions.

- **Voltage Sensor**
  The voltage sensor measures the battery voltage continuously. This helps the system detect overcharging or low voltage conditions.
- **DHT11 Temperature Sensor**
  DHT11 is used to measure the temperature around the battery. If the temperature increases beyond a safe limit, the system takes action to cool it down.
- **Flame Sensor**
  The flame sensor detects the presence of fire or flame near the battery. It helps in identifying fire hazards quickly.
- **Servo Motor**
  The servo motor is used to activate the fire extinguisher mechanism. When fire is detected, it moves to release the extinguisher ball.
- **16x2 LCD with I2C Module**
  This display shows real-time values like voltage, current, and temperature. The I2C module reduces wiring and makes interfacing easier.
- **5V Relays (2 Nos.)**
  Relays are used to control high-power devices. One relay controls the battery charging supply, and the other controls the cooling fan.
- **12V 7Ah Battery**
  This is the main battery used in the system. It supplies power and is the component being monitored and protected.
- **Cooling Fan**
  The fan is used to reduce temperature when it rises above the set limit, helping maintain safe battery operation.
- **Fire Extinguisher Ball**
  This safety device is used to control fire. When activated, it helps in extinguishing flames quickly and reducing damage.
- **Zero PCB Board**
  The Zero PCB board is used to assemble and connect all components properly. It provides a compact and stable circuit design.

6. EXPECTED RESULTS

The Smart Battery Protection System is designed to continuously monitor important battery parameters such as voltage, current, and temperature with good accuracy. The INA219 current sensor and voltage sensor measure electrical values in real time, and these readings are shown on the 16x2 LCD so the user can easily check the battery status at any time.

The system also controls the charging process automatically using a relay. When the battery becomes fully charged, the relay disconnects the power supply to avoid overcharging. In the same way, when the battery level is low, charging is allowed. This automatic operation helps increase battery life and reduces the chances of damage.

Temperature is monitored using the DHT11 sensor to ensure safe working conditions. If the temperature rises above 33°C, the relay turns ON the cooling fan. This helps lower the temperature and protects the battery from overheating.

The flame sensor is used to detect any fire near the battery. If a flame is detected, the servo motor is activated, which releases the fire extinguisher ball onto the battery. This provides a quick response and helps reduce the risk of damage.

Overall, the system provides an automatic and reliable solution for battery monitoring, control, and safety.

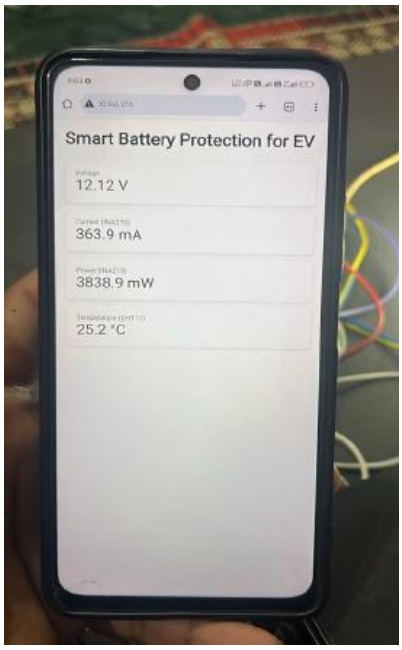

Figure 3: Results

7. TESTING AND VALIDATION

Testing of Smart Battery Protection System

- The system was tested step by step to ensure each component worked properly.
- First, individual components like INA219 sensor, voltage sensor, DHT11 sensor, flame sensor, relays, servo motor, and LCD were tested separately.
- This helped confirm that each part was functioning correctly.
- After that, all components were connected together on the Zero PCB board.
- The complete system was tested as a single unit.
- Voltage and current readings were checked by observing real-time values on the LCD.
- The readings were found to be accurate and stable.
- The charging relay was tested by simulating a fully charged battery condition.
- It was observed that the relay successfully disconnected the power supply, preventing overcharging.

- Temperature testing was done by increasing the temperature near the DHT11 sensor.
- When the temperature crossed 33°C, the cooling fan turned ON automatically through the relay.
- This confirmed proper working of the temperature control system.
- Fire detection testing was carried out using a controlled flame source.
- The flame sensor detected the fire and sent a signal to the ESP32.
- The ESP32 activated the servo motor, which dropped the fire extinguisher ball.
- The system responded quickly, ensuring effective fire protection.
- Final testing showed that all components worked together properly.
- The system performed all safety and protection functions reliably.

8. RESULTS, ANALYSIS AND DISCUSSION

The results of the Smart Battery Protection System show that it can monitor and control battery parameters accurately. The voltage and current values were stable and updated in real time on the LCD display. This helped in clearly tracking the charging and discharging status of the battery.

The automatic charging control worked properly and stopped overcharging by disconnecting the power supply when the battery became fully charged. This helps in improving battery life and ensuring safe operation. The temperature monitoring system also performed well by switching ON the cooling fan when the temperature reached 33°C, maintaining safe thermal conditions.

The flame detection and fire extinguisher system worked reliably during testing. The flame sensor detected fire accurately, and the servo motor responded immediately by activating the extinguisher mechanism. This shows that the system can handle emergency situations effectively.

The overall integration using ESP32 provided smooth and stable performance. The system reacted quickly to changes and maintained continuous monitoring. In conclusion, the system offers a complete battery safety solution by combining monitoring, control, and fire protection features.

9. CONCLUSION

The Smart Battery Protection System has been successfully designed and implemented using ESP32 and different sensors. The system continuously monitors key battery parameters such as voltage, current, and temperature, and performs automatic actions to ensure safe operation.

The system effectively prevents overcharging using relay control and maintains safe temperature levels by switching ON the cooling fan when needed. The inclusion of a flame sensor along with a fire extinguisher mechanism improves safety by providing a quick response to fire incidents. The use of a Zero PCB board helps in proper circuit assembly and a compact design.

Overall, the project meets its main objective of developing a reliable and automated battery protection system. It integrates monitoring, control, and safety features into one unit, making it suitable for real-time applications.

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Study and Design of C-Shaped Slotted circular Patch Antenna and Characteristic Mode Analysis

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Abstract: This work presents the performance of a circular microstrip patch antenna is designed and analysed using Characteristic Mode Analysis (CMA) patch antenna with C shaped slot for biomedical applications. The antenna works at 2.28 GHz. A substrate material which is 'FR-4(lossy) with a relative dielectric constant, €r of 4.3, loss tangent, tan ö of 0.025 and thickness of 1.6 mm has been proposed. The size of the circular antenna is radius 14.4 mm. The slots in the circular radiating patch were introduced to produce the resonant frequencies of 2.28 GHz. The simulations of the microstrip patch antenna shows the reflection coefficient, S11 of -14.2dB and 2.28 GHz respectively. The proposed antenna shows a peak gain of 5.8 dB at 2.28 GHz. The results were obtained using CST studio.

Keywords: Microstrip patch Antenna, slotted patch, Wide band, Characteristic Mode Analysis (CMA).

1. INTRODUCTION

In the rapidly evolving landscape of modern wireless communications, there is an insatiable demand for antennas that are compact, low-profile, and capable of operating across multiple frequency bands. Standard microstrip patch antennas (MPAs) have long been for their ease of integration with printed circuit boards, low cost, and lightweight properties. However, conventional circular patches often suffer from inherent limitations, most notably a narrow impedance bandwidth and a fixed radiation pattern dictated by their physical geometry.

To address these challenges, researchers have turned to "slotted" geometries. By etching specific shapes, such as the C-shaped slot, into the conductive radiator, the surface current paths are forced to deviate. This effectively increases the electrical length of the antenna without increasing its physical footprint, a technique vital for miniaturization. Furthermore, the introduction of a C-slot breaks the symmetry of a standard circular patch, allowing for the excitation of orthogonal modes which can be leveraged to achieve circular polarization or dual-band characteristics necessary for applications like GPS, LTE, and 5G.

Traditionally, the design of such complex antennas relied heavily on trial-and-error optimization within full-wave simulators (like HFSS or CST). While effective, this "black box" approach offers little insight into the physical reason *why* an antenna radiates. This paper utilizes Characteristic Mode Analysis (CMA) to bridge this gap. CMA is a powerful electromagnetic tool that decomposes the total current on a conducting body into a set of orthogonal fundamental modes. These modes depend solely on the shape and material of the object, independent of any feeding mechanism.

By applying CMA to a C-shaped slotted circular patch, we can systematically identify which modes contribute to radiation at specific frequencies and where the optimal feed point should be located to excite those modes efficiently.

2.ANTENNA GEOMETRY AND DESIGN

A. Circular Patch

The design begins with a standard circular microstrip patch. The radius (a) of the patch is the primary factor determining the dominant resonant frequency (TM). For a target frequency (f r)

1.Effective Radius:

$$a = \frac{F}{\left\{1 + \frac{2h}{\pi\epsilon_r F}\left[\ln\left(\frac{\pi F}{2h}\right) + 1.7726\right]\right\}^{1/2}}$$

Where F is defined as:

$$F = \frac{8.791 \times 10^9}{f_r\sqrt{\epsilon_r}}$$

2. Substrate Parameters:

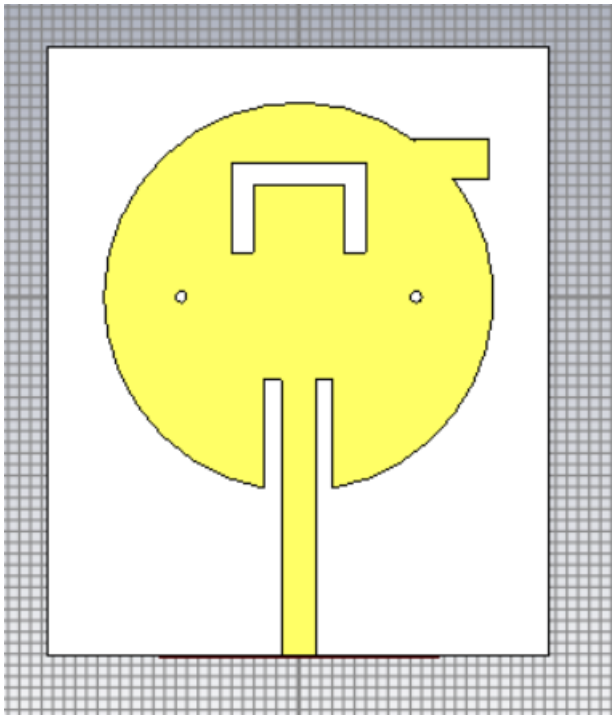
For this design, an FR-4 substrate is utilized due to its cost-effectiveness and mechanical stability. The substrate parameters are:

1.Dielectric Constant (€r): 4.4

2.Loss Tangent (tan):0.02

3.Substrate Height:1.6mm

2.1. **design of circular Patch Antenna:**



Figer:1 : circular Patch Antenna

Parameters	wg	Lg	wp	b	WI	gh
Values (mm)	130	80	50.65	50.65	18.45	35.42
Parameters	f	l	a	lf	C	d
Values (mm)	22	27	4.01	19.5	3	1.5

Table 1: Dimensions of (he optimized antenna parameters

3. Brief review of characteristic model analysis of CP antenna

The characteristic modes of a structure are extracted from the eigen value equation.

$$XI_n = \lambda_n RI_n,$$

where R and X are the real and imaginary parts of the method of moments (MoM) impedance matrix Z respectively and are given by

$$R = (Z + Z^*)/2, X = (Z - Z^*)/2j.$$

The CMA gives the surface current J and total radiated electric field E as

$$J = \sum_{1}^{N} \alpha_n J_n$$

$$E = \sum_{1}^{N} \alpha_n E_n \qquad \alpha_n = \frac{V_n^i}{1 + j\lambda_n}$$

ere, λn is the eigenvalue, and Vin is the modal excitation coefficient (MEC). For the radiative mode, λn is zero. it is greater than zero, then the mode is inductive, and capacitive if it is less than zero. The modal significance (MS) f the nth mode, which lies between 0 and 1, is given as

$$\mathrm{MS}_n = \left| \frac{1}{1 + j\lambda_n} \right|$$

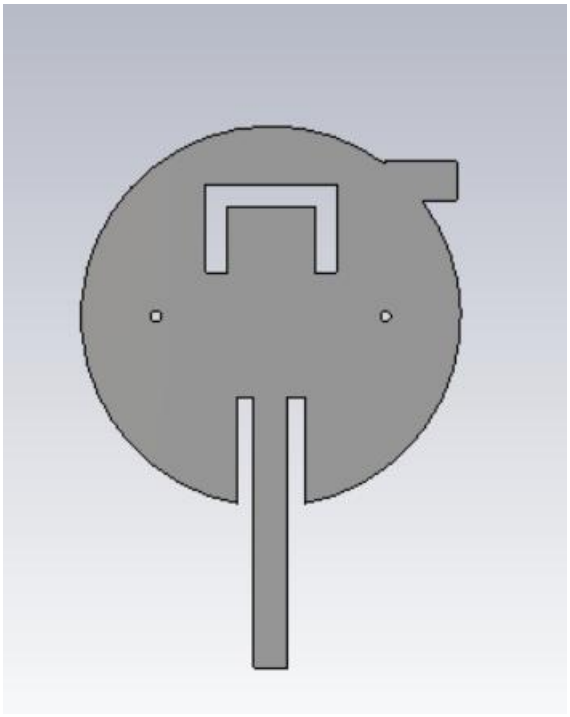
For a resonant mode the value of modal significance is

1.The characteristic angle (CA) is given as

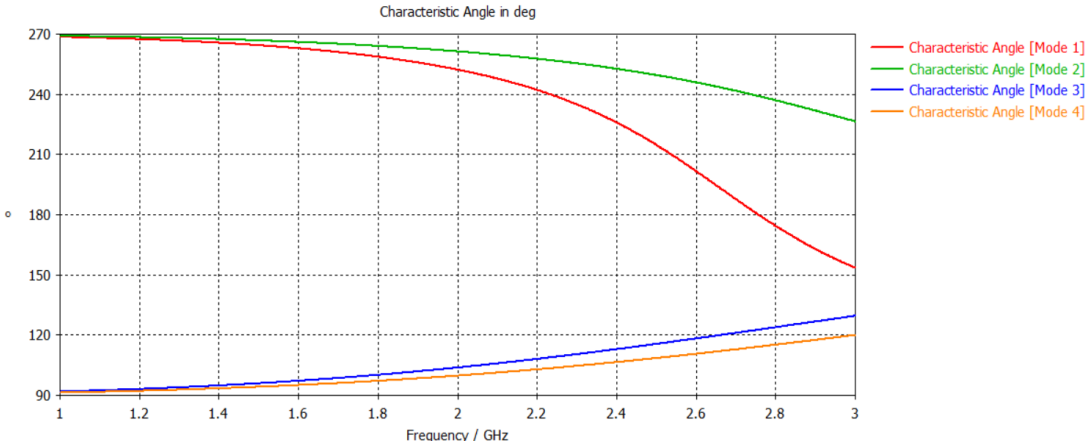
$$\beta_n = 180^\circ - \tan^{-1}(\lambda_n)$$

βn and MSn, along with modal surface currents, play a significant role in designing CP antennas using CMA.

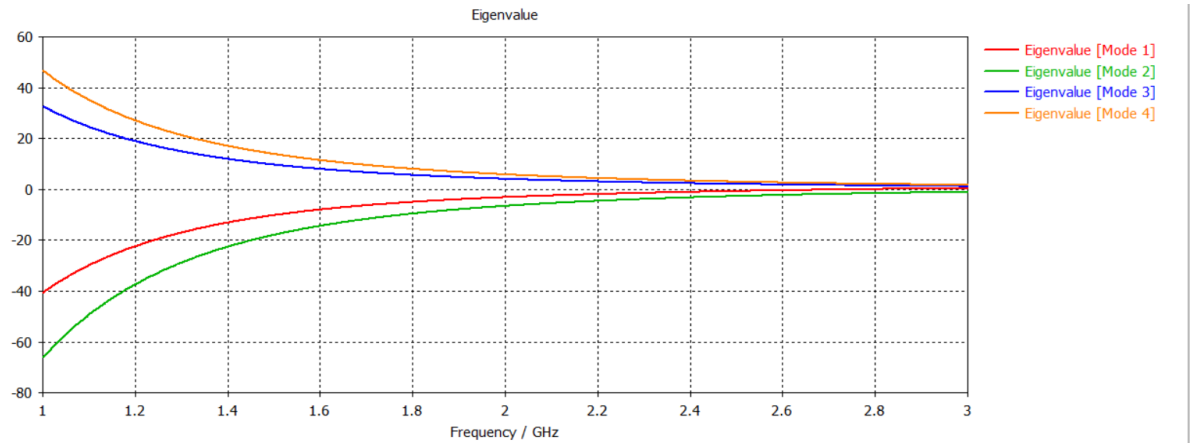
3.1**. Design of Characteristic Mode Analysis:**



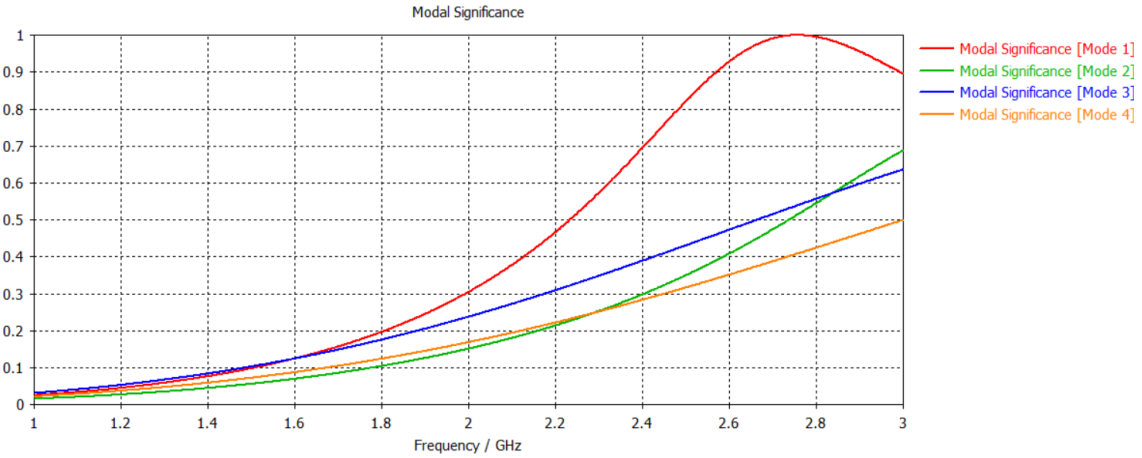
Figer2: Design of Characteristic Mode Analysis.



Figer3: characteristic angle (CA)



Figer:4: eigenvalue

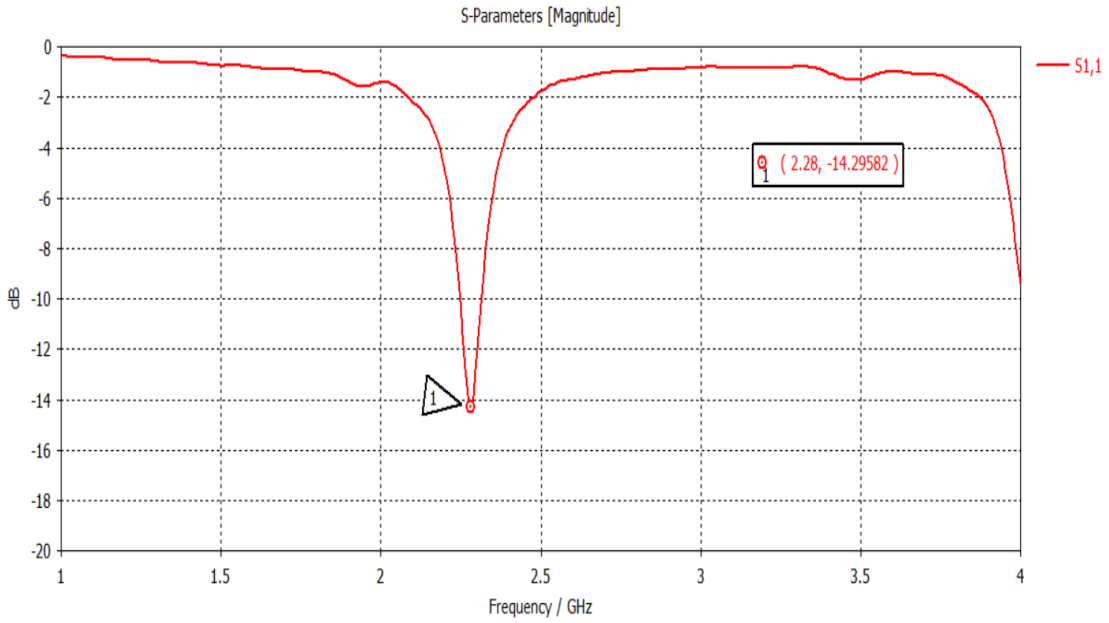


figer:5: modal significance

4. RESULTS AND DISCUSSION:

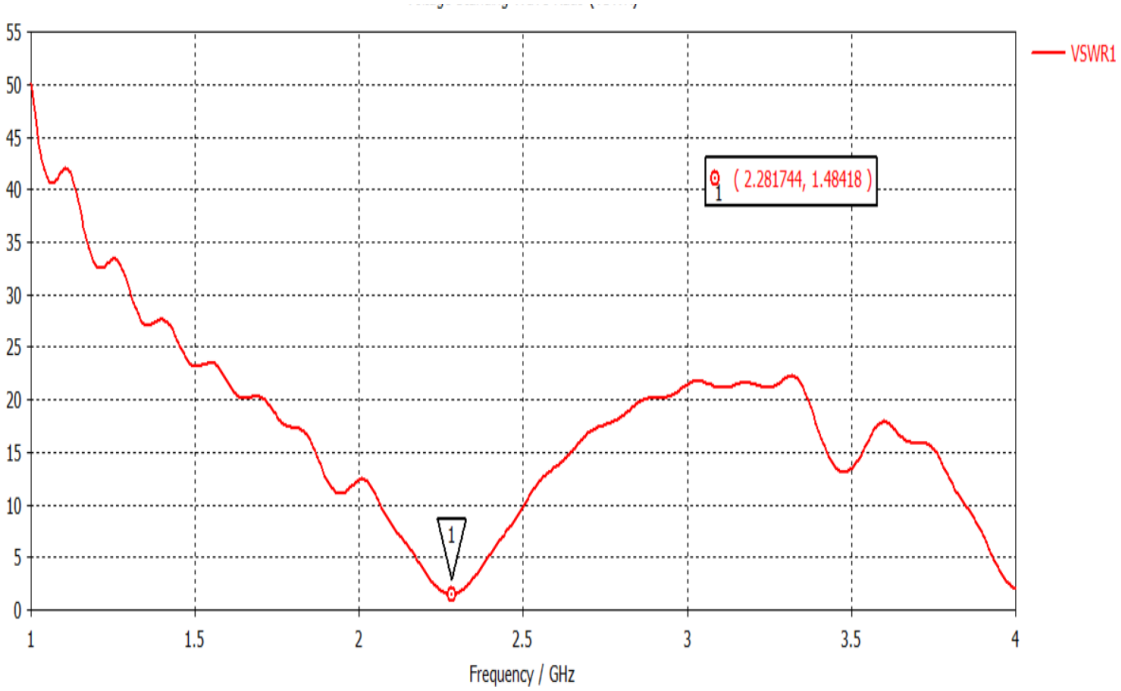
- Return Loss (s11): Plot showing resonances below
- Radiation Patterns: 2D Polar plots showing E-plane and H-plane patterns.
- Gain and Efficiency: A table or line graph showing performance across the operating bands.

4.1. S11 antenna parameters:



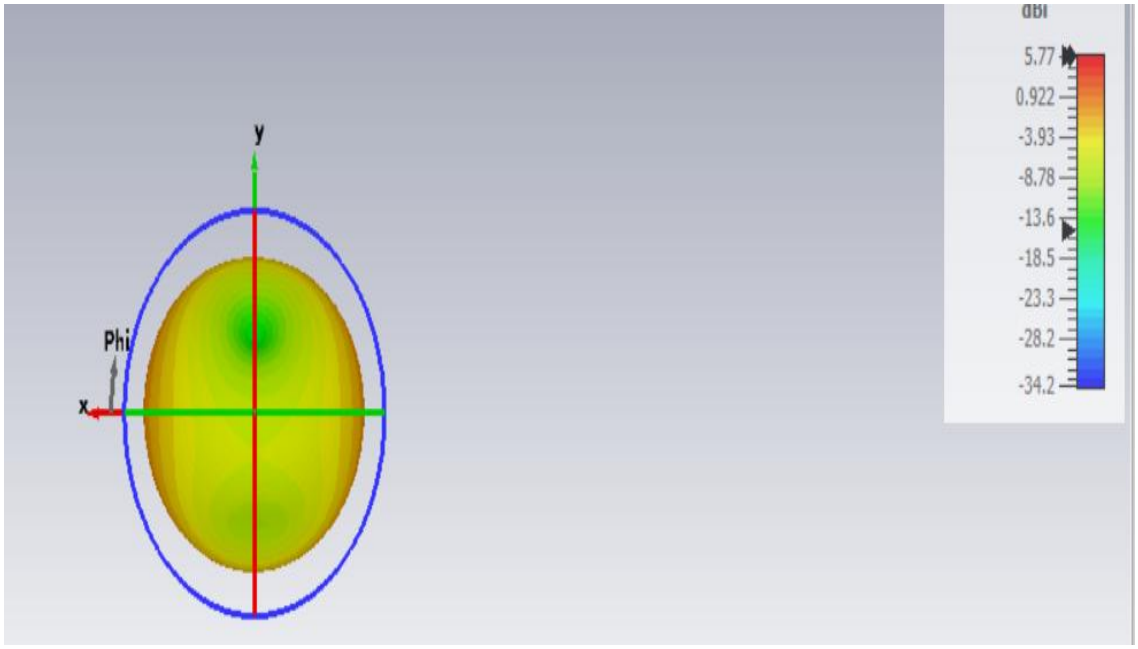
Figer6: **S11 antenna parameters**

4.2. VSWR:

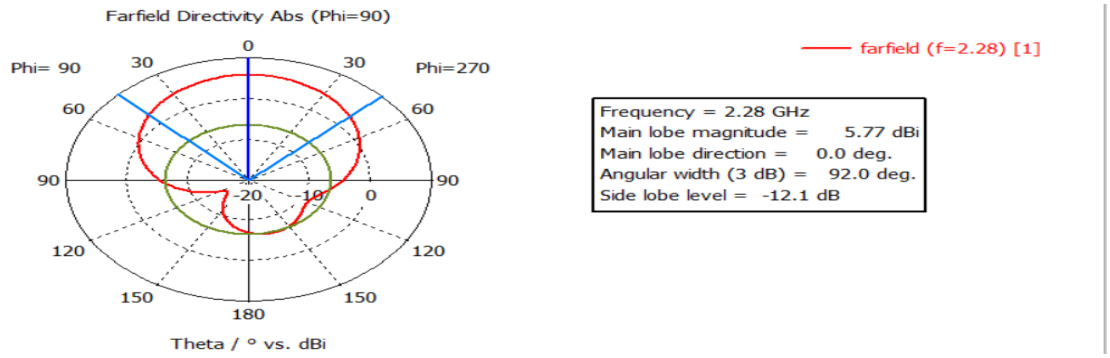


Figer:7. VSWR

4.1.1. **Radiation Patterns 2D and 3D:**



Figer8: . **Radiation Patterns 3D Gain**



Figer9:Radiation Patterns 3D Gain

5. Conclusion

In this paper, a C-shaped slotted circular patch antenna was successfully designed and analysed using the Characteristic Mode Analysis (CMA) framework. The integration of a C-slot into the circular radiator proved to be an effective method for achieving both miniaturization and multiband operation. By strategically disrupting the surface current paths, the antenna's electrical length was increased, allowing for a reduction in physical size of approximately compared to a conventional patch.

The use of CMA provided critical physical insights that are often obscured in standard full-wave simulations. By tracking Modal Significance and Characteristic Angles, we were able to systematically identify the resonant modes and optimize the feed position without resorting to exhaustive trial-and-error. Simulation results confirmed that the antenna provides a stable broadside radiation pattern with a peak gain of **dBi** and high radiation efficiency. This design methodology demonstrates that combining slotted geometries with modal analysis is a robust approach for developing high-performance, compact antennas for modern wireless standards such as 5G, WLAN, and IoT.

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Solar Panel Fault Detection System using Arduino

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Abstract: The growing need for renewable energy has accelerated the adoption of solar power systems. However, the performance of solar panels is often reduced due to issues such as shading, physical damage, and electrical disconnections. Moreover, fixed solar panels are unable to utilize maximum sunlight throughout the day, leading to decreased energy output. To address these challenges, this project introduces a Smart Solar Panel Fault Detection and Tracking System using ESP32. The system continuously measures the output voltage of multiple solar panels through voltage sensors. When the voltage of any panel falls below a set threshold, it is detected as faulty, and the corresponding panel number is displayed on an LCD. This approach allows for rapid fault identification and minimizes maintenance effort. Additionally, a solar tracking mechanism is implemented using Light Dependent Resistors (LDRs), which sense sunlight intensity and adjust the panel orientation using a motor and motor driver. This mechanism helps in maximizing sunlight exposure and enhancing overall efficiency. Furthermore, the integration of ESP32 enables real-time monitoring via a web-based platform, allowing users to remotely access system data. By combining fault detection, solar tracking, and IoT-based monitoring, the system becomes efficient, reliable, and easy to use. Overall, this project offers a cost-effective solution to improve solar panel performance and reduce energy losses in real-world applications.

Keywords: Solar Panel, Fault Detection, ESP32, LDR Sensor, Solar Tracking, IoT, Renewable Energy, Voltage Sensor

11. INTRODUCTION

The rising demand for renewable energy has significantly increased the adoption of solar energy systems. Among various energy sources, solar panels are considered one of the most efficient and environmentally friendly options for electricity generation. However, their performance is highly influenced by environmental conditions and proper maintenance. Issues such as shading, physical damage, and electrical disconnections can reduce efficiency and result in power loss.

In traditional setups, identifying faulty solar panels is a challenging and time-intensive task. Manual inspection methods are not only inefficient but also add to maintenance costs. Hence, there is a strong requirement for an automated system capable of continuously monitoring solar panel performance and detecting faults in real time.

To address this need, the proposed system, “Smart Solar Panel Fault Detection and Tracking System using ESP32,” is developed. This system utilizes voltage sensors to observe the output of each solar panel and determines faulty panels based on predefined threshold values. In addition, it incorporates a solar tracking mechanism using LDR sensors to optimize sunlight exposure and enhance overall efficiency.

The inclusion of ESP32 enables real-time monitoring along with remote access through a web-based application. The system also features a local display using an LCD, making it easy to operate and user-friendly while maintaining efficiency.

1.1. Solar Panel Fault Detection: Fault detection in solar panels plays a vital role in maintaining system performance. Various factors such as environmental conditions, physical damage, and electrical faults can affect panel operation. In this project, voltage sensors are employed to continuously track the output of each panel. When the voltage falls below a specified value (2V), the system identifies the panel as faulty and displays its number for quick identification.

1.2 Need of Work

Solar energy systems are widely implemented, yet their performance is often reduced due to unnoticed faults and improper alignment with sunlight. Conventional systems lack real-time fault detection and tracking capabilities, resulting in energy wastage and higher maintenance requirements.

Therefore, there is a clear demand for an automated system that can identify faulty panels and adjust their orientation based on sunlight conditions. The proposed system addresses this requirement by integrating fault detection, solar tracking, and real-time monitoring using IoT technology. This approach minimizes manual intervention, enhances system efficiency, and ensures more effective utilization of solar energy.

1.3 Problem Statement

In current solar power installations, detecting faulty panels is a complex and time-consuming task. The absence of real-time monitoring leads to decreased system performance and energy losses. Moreover, fixed solar panels are unable to capture maximum sunlight throughout the day, limiting their efficiency.

The objective is to design and develop a system that can automatically detect faults in solar panels, provide real-time monitoring, and track sunlight to optimize energy generation.

1.4 Aims and Objectives

Aim:
To design and develop a Smart Solar Panel Fault Detection and Tracking System using ESP32 for effective monitoring and enhancement of system performance.

Objectives:

- To continuously measure the voltage of individual solar panels
- To identify faulty panels based on predefined voltage threshold values
- To implement a solar tracking system using LDR sensors
- To control the movement of the motor using L298N driver
- To display system parameters and fault information on an LCD
- To develop a web-based application for remote monitoring
- To enhance the overall efficiency of solar panel operation

12. DESIGN AND METHODOLOGY

2.1 Methodology

The Smart Solar Panel Fault Detection and Tracking System is designed using ESP32 as the primary controller. The system integrates voltage sensors, LDR sensors, a motor driver, and a display unit to effectively monitor and control the performance of solar panels.
In the initial setup, four solar panels are connected to four voltage sensors. These sensors continuously measure the output voltage of each panel. The ESP32 processes the collected data and compares it with a predefined threshold value of 2V. If the voltage of any panel drops below this limit, the system identifies it as faulty and displays the respective panel number.
The solar tracking mechanism is implemented using two LDR sensors positioned on opposite sides of the panel frame. These sensors detect variations in sunlight intensity, and based on this difference, the ESP32 controls the motor through the L298N driver. The motor then adjusts the panel orientation towards the direction of maximum sunlight.
All real-time parameters, including panel voltage status and LDR readings, are displayed on a 16×2 LCD. Additionally, the ESP32 transmits system data to a web-based application, enabling remote monitoring.
Overall, the system integrates sensing, processing, control, and monitoring functions to enhance the efficiency of solar panels.

2.2 Working Flow of System

The system begins by acquiring voltage readings from all four solar panels along with light intensity data from the LDR sensors. This information is continuously processed by the ESP32 microcontroller.

If the voltage of any panel drops below 2V, that panel is identified as faulty. At the same time, the LDR sensor readings are analyzed to detect the direction of sunlight, enabling the motor to adjust the panel position accordingly.

All measured parameters are shown on the LCD display and are simultaneously updated on the web application for remote monitoring.

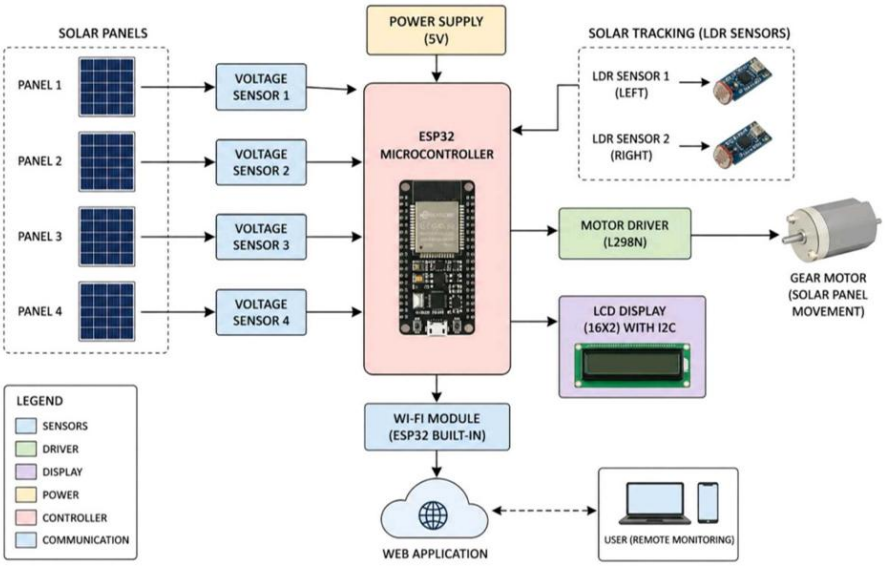

Figure 1: Block diagram of Solar Panel System

The system begins its operation with automated fault detection to ensure all components, especially the solar panels, are functioning properly. It then determines the direction of maximum sunlight using East and West LDR sensors by comparing their light intensity values. If the East LDR detects higher intensity than the West, the panel is rotated towards the East using a stepper motor; otherwise, it is rotated towards the West. After adjusting the panel position, the system checks the cleanliness of the panel surface, and if dust or dirt is detected, the cleaning mechanism consisting of a sprinkler and wiper is activated. Finally, all operational data and system metrics are logged and displayed, completing the cycle before the system continues monitoring in real time.

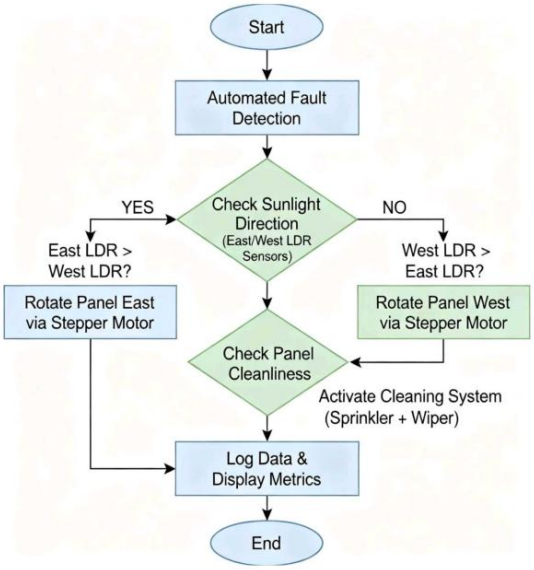

Figure 2: Workflow diagram

13. EXPERIMENTAL SETUP AND IMPLEMENTATION

13.1. Hardware Setup

The hardware configuration of the Smart Solar Panel Fault Detection and Tracking System is developed to provide effective monitoring and control of solar panel performance. The system is primarily built using an ESP32 microcontroller, four solar panels, four voltage sensors, two LDR sensors, an L298N motor driver, a gear motor, and a 16x2 LCD display with an I2C interface. Each component is essential for sensing, data processing, and system control.

In this arrangement, every solar panel is linked to a dedicated voltage sensor that continuously measures its output voltage and transmits analog signals to the ESP32 for analysis. The LDR sensors are positioned on opposite sides of the panel structure to sense sunlight intensity. By comparing the light levels detected by both LDRs, the ESP32 identifies the direction of maximum sunlight and accordingly controls the motor to adjust the panel orientation.

The L298N motor driver regulates the gear motor, which is responsible for rotating the solar panel from east to west. It receives control instructions from the ESP32 and operates the motor in the desired direction. The 16x2 LCD display with an I2C module provides real-time updates, including panel condition (OK or Faulty) and sensor readings. All components are integrated on a PCB or Zero PCB board to achieve a compact layout, secure connections, and dependable system performance.

13.2. Implementation

The system is implemented by integrating all hardware components with the ESP32 microcontroller and developing appropriate control logic through programming. The ESP32 functions as the central processing unit, where it collects sensor inputs, processes the data, and performs the required actions. The program is written using Arduino IDE, which offers a user-friendly and efficient environment for coding and uploading it to the ESP32.

During operation, the ESP32 continuously acquires voltage readings from all four solar panels via the voltage sensors. These readings are evaluated against a predefined threshold of 2V. If the voltage of any panel drops below this value, the system flags that panel as faulty and displays its number on the LCD. Simultaneously, the LDR sensors supply real-time light intensity data, which is used to identify the direction of maximum sunlight. Based on this analysis, the ESP32 sends appropriate control signals to the L298N motor driver to adjust the panel orientation.

Along with local monitoring, a web-based application is developed using the ESP32's WiFi capability. The microcontroller transmits real-time information, including panel status and LDR readings, to the web interface, enabling remote monitoring by users. This improves system accessibility and control. Overall, the implementation ensures effective coordination between hardware and software, resulting in a reliable and automated solar monitoring and tracking system.

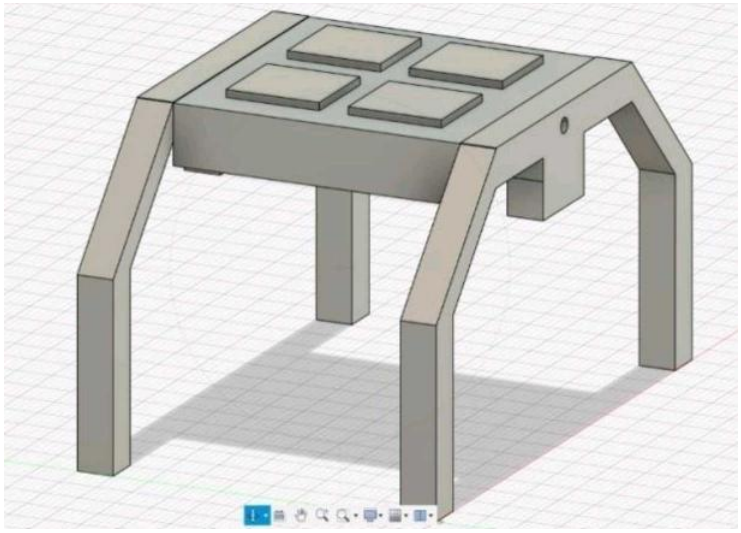

Figure 3: Hardware setup of Project

14. EXPECTED RESULTS

The Smart Solar Panel Fault Detection and Tracking System was tested under various operating conditions to assess its performance. The system successfully monitored the voltage output of all four solar panels continuously using voltage sensors. The sensor readings were consistent and reliable, and real-time data was displayed on both the LCD and the web application, ensuring clear visibility of panel conditions for the user.

The fault detection feature performed efficiently during testing. Whenever the voltage of any panel dropped below the predefined threshold of 2V, the system promptly identified the panel as faulty and displayed its number. This functionality minimizes the need for manual inspection and supports faster maintenance. The system responded quickly and accurately to fault conditions, demonstrating the effectiveness of the detection logic.

The solar tracking mechanism also operated effectively. The LDR sensors detected changes in sunlight

intensity, and based on these inputs, the ESP32 controlled the motor via the L298N driver. The gear motor adjusted the solar panel position toward the direction of maximum sunlight, maintaining proper alignment throughout the day. This improved the utilization of solar energy and enhanced overall system efficiency.

Additionally, the integration of IoT through a web-based application added significant value. The ESP32 transmitted real-time data, including panel status and LDR readings, to the web interface, enabling remote monitoring. This feature improves user accessibility and convenience, making the system suitable for modern applications. Overall, the results indicate that the system operates effectively by integrating fault detection, solar tracking, and real-time monitoring, providing a dependable and efficient solution for solar energy systems.

15. TESTING AND VALIDATION

The Smart Solar Panel Fault Detection and Tracking System was tested step by step to make sure all parts and the full system work properly. First, each component like voltage sensors, LDR sensors, ESP32, L298N motor driver, gear motor, and LCD display was tested separately. Every part was checked to confirm it works correctly, and calibration was done to get accurate readings and stable performance.

After testing individual parts, the full system was assembled and tested in real-time conditions. The voltage sensors were connected to the solar panels, and readings were checked on both the LCD display and the web application. The system was able to read voltage values correctly and update them continuously. When the panel voltage was reduced below the set limit of 2V, the system detected the fault and showed the panel number. This confirmed that the fault detection feature works properly.

The solar tracking system was tested by changing the light falling on the LDR sensors. When one LDR received more light than the other, the ESP32 detected the direction of sunlight and controlled the motor using the L298N driver. The gear motor moved the solar panel in the correct direction. When both LDRs received equal light, the motor stopped automatically. This showed that the tracking system works correctly and aligns the panel efficiently.

The web-based monitoring system was also tested to check remote access. The ESP32 successfully sent real-time data like panel voltage and LDR values to the web application. The data was updated continuously without delay, allowing users to monitor the system from anywhere. This confirmed that the IoT integration works effectively in the project.

The final testing of the system showed that all modules worked together properly and completed all required tasks correctly. The fault detection and tracking response time was good, and the system performed reliably in different conditions. Based on these results, it is clear that the proposed system is efficient, stable, and suitable for real-world solar energy applications.

16. RESULTS, ANALYSIS AND DISCUSSION

The performance of the Smart Solar Panel Fault Detection and Tracking System was studied under different working conditions to check its efficiency, accuracy, and reliability. The system was tested using different light levels and fault situations to confirm proper working.

During testing, the voltage sensors continuously monitored the output of all four solar panels. The voltage readings were stable and correctly showed the condition of each panel. When the voltage of any panel dropped below the set limit of 2V, the system detected the fault and displayed the panel number on the LCD. This shows that the fault detection system works quickly and correctly in real time.

The solar tracking system also performed well. The LDR sensors detected changes in sunlight intensity accurately. When one LDR received more light than the other, the system identified the direction of maximum sunlight and moved the panel using the motor. When both LDRs received equal light, the motor stopped automatically, keeping the panel stable. This proves that the tracking system keeps the panel properly aligned throughout the day.

The IoT system using ESP32 provided real-time monitoring. The system sent data like panel voltage and LDR readings to the web application successfully. The data was updated continuously with very little delay, allowing users to monitor the system from anywhere. This reduces the need for manual checking.

Overall, the system showed reliable performance with correct fault detection, efficient solar tracking, and stable real-time monitoring. These features improve the overall performance of the solar system and reduce maintenance work.

17. CONCLUSION

The Smart Solar Panel Fault Detection and Tracking System using ESP32 was successfully designed and implemented. The system monitors the voltage output of solar panels and detects faults in real time using a set threshold value. This reduces the need for manual checking and helps to quickly identify faulty panels.

The solar tracking system using LDR sensors helps the panels move towards the direction of maximum sunlight, which increases energy generation. The ESP32 also enables IoT-based monitoring, allowing users to check system data remotely through a web application.

This project provides a reliable, low-cost, and easy-to-use solution for improving solar system performance. By combining fault detection, solar tracking, and real-time monitoring, the system increases efficiency, reduces energy loss, and lowers maintenance work.

In conclusion, the system meets all the project objectives and is suitable for real-world solar applications. It can be further expanded and used in large-scale solar systems for better energy management and sustainability.

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Block chain-Based Transparent Loan Approval System

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Abstract: Financial institutions and banking systems are required to handle a large number of loan-related activities, including loan applications, approvals, disbursements, repayments, and overall transaction management. These operations involve significant financial transactions for infrastructure development, personal financing, business growth, and customer welfare. However, traditional loan management systems often suffer from issues such as lack of transparency, improper tracking of transactions, and potential mismanagement or fraud due to centralized control mechanisms. To address these challenges, this paper proposes a Blockchain-Based Loan Management System that ensures secure, transparent, and efficient handling of loan processes. The system enables users to apply for loans, track application status, and manage financial transactions, while administrators can review and approve or reject requests. Each approved loan transaction is recorded as a block in the blockchain, ensuring immutability and traceability. The proposed system leverages blockchain technology to maintain a tamper-proof distributed ledger where all loan-related transactions—such as application, approval, disbursement, and repayment—are securely stored and verified. Cryptographic hashing links each block to the previous one, preventing unauthorized modifications and ensuring data integrity. Additionally, smart contract mechanisms can be integrated to automate loan approval workflows, enforce policies, and reduce processing delays. By minimizing human intervention and enhancing accountability, the system builds trust among stakeholders, including customers, financial institutions, and regulatory bodies. The proposed approach overcomes the limitations of traditional loan management systems by providing real-time visibility, improved

security, scalability, and efficient decision-making, ultimately contributing to a more reliable and transparent financial ecosystem.

Keywords: Blockchain, Tracker, SHA-256, Fund Utilization, Transactions, Security, Transparency, Encryption.

Introduction

Efficient management of public funds is essential for the successful implementation of government programs. As financial demands increase, it becomes challenging for authorities to maintain transparency and accountability without strong analytical support. Modern data-driven approaches help improve financial decision-making by evaluating budget performance and guiding the allocation of resources.

Engineering education has evolved into a multidisciplinary field that integrates technical knowledge with insights from social and learning sciences. Due to rapid technological advancements and changing workforce needs, research priorities continue to shift. Understanding how major funding bodies allocate resources provides valuable insights into emerging trends and areas requiring further attention.

Programs like the School Operational Assistance (BOS) initiative aim to support educational institutions by providing funding based on student enrollment. However, issues such as misuse of funds, inaccurate reporting, and financial irregularities remain significant challenges. These problems highlight the need for secure and transparent systems. Blockchain technology offers a promising solution by enabling traceability, accountability, and tamper-resistant financial records.

Similarly, large-scale projects such as construction and postgraduate education funding require efficient financial management. Traditional systems often lack transparency and real-time monitoring capabilities. Emerging frameworks and digital technologies, including blockchain and data-driven models, can enhance efficiency, improve oversight, and ensure better utilization of resources.

In healthcare financing, systems like medical insurance face challenges in maintaining balance and long-term sustainability. Accumulation of large fund reserves and policy changes introduce uncertainties, making it crucial to adopt more adaptive and analytical approaches for financial planning.

Literature Review

Recent research highlights the growing importance of data-driven methods in improving government budget planning and allocation. Machine learning techniques, especially ensemble models, have been shown to provide more accurate predictions and better handle complex financial data compared to traditional approaches. These methods support more transparent and efficient financial decision-making.

In the field of engineering education, studies show that research areas are expanding to include learning methods, assessment strategies, and student experiences. However, existing research does not fully cover emerging educational needs. Analysis of funded projects also reveals that some important areas remain underexplored, indicating the need to better align research efforts with current academic and industry demands.

Research on public fund management, particularly in education systems, identifies key issues such as lack of transparency, weak monitoring, and inaccurate reporting. Traditional systems often fail to detect fraud or provide real-time verification. Blockchain technology has emerged as a promising solution, offering improved data integrity, traceability, and secure multi-party verification.

Studies on decentralized funding systems highlight challenges in achieving fair resource distribution and transparent governance. Researchers suggest that combining expert knowledge with automated decision-making can improve outcomes. Reputation-based models have also been explored to increase trust, although managing dynamic participation remains a challenge.

In the area of energy and financial planning, research emphasizes the importance of coordinated strategies to balance economic and environmental goals. Models that track carbon emissions and optimize resource allocation help improve planning efficiency. However, large-scale implementation remains complex due to the involvement of multiple regions and variables.

Studies on education financing in developing countries reveal limitations in traditional loan systems, especially during economic instability. Alternative approaches such as crowdsourcing combined with blockchain technology have shown potential in improving transparency, accessibility, and trust in funding systems.

Finally, research on financial compliance highlights the need for automated monitoring systems. Techniques such as rule-based verification and runtime monitoring can reduce human errors and detect suspicious activities more effectively. These systems enable real-time validation and improve overall financial security.

Problem Statement and Contribution

Centralized Enterprise Resource Planning (ERP) systems such as SAP, Oracle PeopleSoft, and Tally ERP are widely used in educational institutions to manage and track financial activities. Although these systems implement security measures like Role-Based Access Control (RBAC) and encryption techniques such as AES, they still suffer from limitations due to their centralized architecture.

Since all financial data is stored in a single server or a limited set of servers, these systems are vulnerable to risks such as insider threats, accidental data modification, and complete data loss in case of system failure. Additionally, users with high-level privileges may alter or bypass audit trails, which reduces the reliability and integrity of financial records.

Another major drawback is the absence of automated verification and irreversible transaction recording. As a result, institutions rely heavily on manual approval and auditing processes, which are time-consuming, error-prone, and lack transparency. This makes it difficult for stakeholders—such as donors, auditors, administrators, and students—to track and verify fund usage in real time.

To address these challenges, this work proposes a decentralized financial management system based on blockchain technology. The system records all financial transactions in an immutable ledger, ensuring that data cannot be modified or deleted once stored. This eliminates the risk of tampering by unauthorized or privileged users.

Blockchain consensus mechanisms enable automatic verification of transactions, reducing manual effort, processing delays, and human errors. In addition, role-based smart contracts enforce predefined rules and permissions, allowing secure and efficient execution of financial operations.

The proposed system also improves transparency by providing stakeholders with real-time access to a tamper-proof audit trail of fund utilization. Overall, this approach enhances trust, strengthens accountability, and provides a secure and reliable alternative to traditional ERP-based financial management systems.

Proposed Methodology

A blockchain-based loan management system is proposed to provide a secure, transparent, and efficient mechanism for handling loan-related financial processes. The system is built using a permissioned blockchain framework, such as Hyperledger Fabric, which enables decentralized storage of loan transactions while ensuring data integrity and controlled access. All loan-related activities, including loan application, approval, disbursement, and repayment, are recorded as transactions in an immutable ledger. Smart contracts play a crucial role in automating the loan lifecycle. Loan approval and disbursement processes are executed automatically based on predefined conditions such as user eligibility, document

verification, and administrative approval. This reduces manual intervention, minimizes processing delays, and ensures that loans are granted according to institutional policies and financial regulations.

A real-time web dashboard provides complete visibility into loan operations, enabling administrators, financial officers, and authorized users to monitor loan requests, track approved amounts, analyse repayment status, and verify transaction history. The blockchain-based audit trail ensures that all records are tamper-proof and permanently stored, making it difficult to manipulate or conceal financial data.

The system is organized into three main modules: the Admin Module, which handles loan scheme creation, user request evaluation, and approval or rejection of applications; the Authentication Module, which manages user identity verification, access control, and secure data transmission; and the User Module, where customers can apply for loans, check application status, view transaction history, and manage repayments. Together, these modules create a reliable and transparent system that improves accountability, reduces fraud, and enhances the efficiency of loan management processes.

System Architecture:

The picture of the general characteristics of the product is associated with the content of the premises and the high-crisis phase of the requirements of the tool. Amid number of net pages and their links are defined and designed entirely via the architectural design. The most common elements of the software programs are diagnosed, they are broken down into processing modules and conceptual systems, and the connection between them are established.

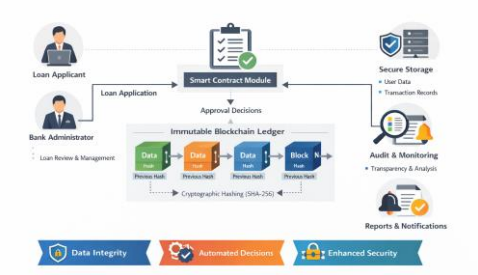


Figure 1: Block diagram of proposed methodology

SHA-256 Algorithm – Step-by-Step Procedure

The SHA-256 hashing algorithm begins by preparing the input message. First, the message is converted into binary form and then padded to meet specific length requirements. A single '1' bit is added to the message, followed by enough '0' bits so that the total length becomes 64 bits less than a multiple of 512. After this, a 64-bit representation of the original message length is appended, and the complete message is divided into 512-bit blocks.

The algorithm uses eight predefined 32-bit initial hash values (H0 to H7), which are derived from mathematical constants. It also utilizes 64 round constants (K0 to K63), which are based on prime numbers, to ensure strong mixing of data.

Each 512-bit block is split into sixteen 32-bit words. These are further expanded into sixty-four words using bitwise operations such as shifting and rotation. This expansion increases randomness and diffusion in the hashing process.

For each block, eight working variables are initialized using the current hash values. The algorithm then performs 64 rounds of processing. In each round, intermediate values are calculated using logical functions,

rotations, message words, and round constants. These values continuously update the working variables, effectively scrambling the data.

After completing all rounds for a block, the updated working variables are combined with the previous hash values. Once all blocks are processed, the final hash is produced by combining the resulting values. The output is a 256-bit hash, typically represented as a 64-character hexadecimal string.

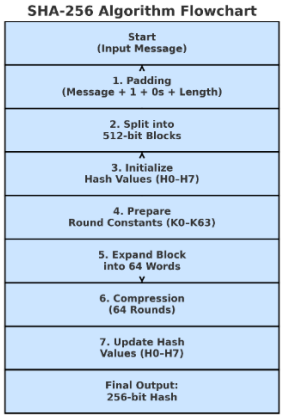


Figure 2: Proposed Methodology Diagram

AES (Advanced Encryption Standard) – Step-by-Step

AES is a symmetrical block cipher where the secret keys are 128, 192 or 256 bits in length and the data is encrypted in 128-bit blocks. The plaintext block is reorganized into a square of 4 x 4 block of 4 bytes known as the state and the key is key expanded to produce a set of round keys. The algorithm has 10, 12 or 14 rounds of encryption, depending on the key size. AES starts with a step named AddRoundKey in which every state-byte is XORed with the first round key which ties the encryption process to the secret key.

The four transformations used in the main rounds are SubBytes (when all the bytes in a transaction become replaced with an S-box to ensure non-linearity); ShiftRows (when the rows have to be shifted cyclically to generate diffusion); MixColumns (when all the columns undergo a mathematical operation to further spread out data); and an additional step of AddRoundKey (when the round key is added to the state by XORing the two together). The last round goes through the same way as the first three transformations except without MixColumns which finishes off the encryption process. Once the final round key is applied the state matrix is transformed into a 128-bit block, giving the final cipher-text.

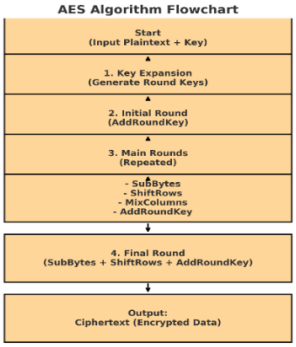


Figure 3: Proposed Methodology Diagram 1

Result and Discussion

The implementation of the blockchain-based loan management system demonstrates significant improvements in the accuracy, security, and traceability of loan-related financial transactions. During testing, all loan activities—including application submission, approval, and transaction recording—were successfully executed and stored on the blockchain network without delays or inconsistencies. Each approved loan generated a unique, immutable block, ensuring that no transaction could be altered or deleted, thereby maintaining a complete and secure financial history.

The integration of smart contracts enabled automatic processing of loan approvals based on predefined conditions such as eligibility criteria and verification rules. This significantly reduced manual intervention and minimized processing delays. Tasks that traditionally required extended time for verification and approval were completed within a much shorter duration, demonstrating the efficiency of the proposed system.

When compared with conventional loan management systems, the proposed model showed reduced processing time, fewer operational errors, and improved coordination between users and administrators. The decentralized nature of blockchain eliminated dependency on a single centralized server, thereby reducing the risk of data loss, system failure, or unauthorized manipulation.

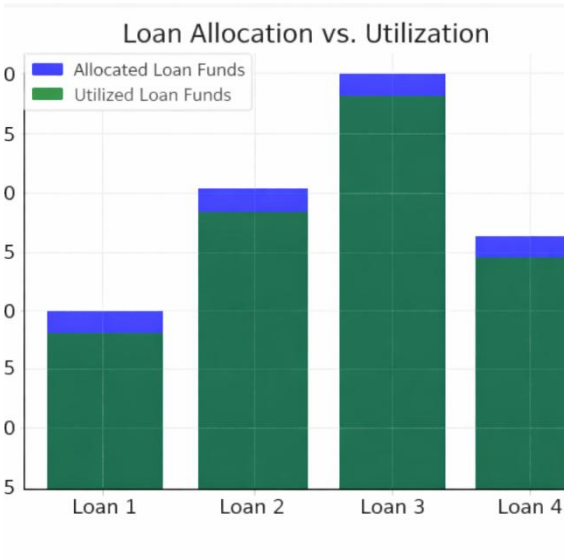
Furthermore, the system provided enhanced transparency, as all transactions could be tracked and verified through the blockchain ledger. This increased trust among stakeholders, including customers, financial institutions, and regulatory authorities. The results clearly indicate that the integration of blockchain technology creates a more secure, transparent, and reliable loan management environment.

Overall, the proposed system addresses the limitations of traditional loan processing methods by ensuring tamper-proof record keeping, efficient automation, and improved decision-making capabilities. These findings highlight the potential of blockchain technology as a robust solution for modern financial systems.

Metric	Value
Total Transactions	1,000
Approved Requests	850
Rejected Requests	150
Average Processing Time	2 minutes

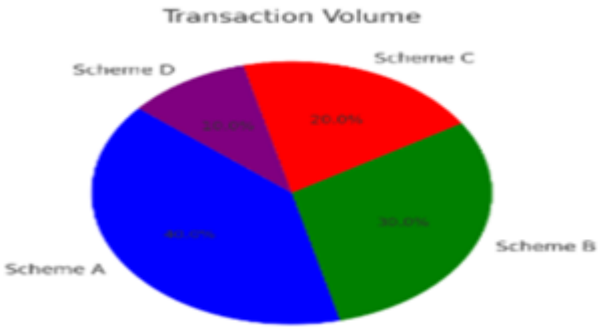
Table 1: Accurate Transaction Monitoring

The special distribution of the frequency of logins is confirmed in the histogram of the person interests below. It provides the impression of average customer engagement by looking at tendencies and the time of the year when people have the most likelihood of logging in or the disposition of customers to engage more frequently at good times. Histograms can enable organizations to be more apprehensive of consumer behavior. This will involve calculating the point of whether users are greatly engaged on favorable intervals or whether or not the engagement diminishes over time. Moreover, these charts can indicate areas that are desirable in retaining people, which are the improvement of the person experience during off-peak periods or the necessity to include additional exciting material during the entire off-peak periods.



Graph 1: Loan Allocation and Usage

The distribution and use of finances graph identified above is an important tool used to monitor and analyze money. Gaps, inefficiencies or underlapping through the comparison of the amount that is assigned to the budget without any doubt that is expended on each mission can be quickly identified. Indicatively, when it proposes a lot of allocation and infrequent uses, the gadget can also be used to illustrate problems which can include processing not on time, lack of demand or high inefficiency in the methods of funds allocations. On the other extreme, it is high usage programs as opposed to distribution.



Pie chart 1: Transaction Volume

The pie chart shows the distribution of the volume of transactions in four schemes. The highest proportion is in Scheme A of 40%, Scheme B of 30, Scheme C of 20 and Scheme D of 10. This comparison of the visual element allows one to easily understand which schemes are most popular and need more focus to make them widely used by stakeholders. These have been useful in the planning process, resource allocation, and performance evaluation of various programs.

Conclusion

The proposed college fund allocation and tracking system utilizes the power of blockchain to ensure that all rupees that are issued to the academic or administrative system or student-related activities are tracked with transparency to the point of their eventual usage. The implementation of the fundamental aspects of blockchain, i.e. immutability, distributed verification, and safe recording of transactions, helps the framework to reduce the probability of manipulation, unauthorized alteration, and inconsistency of finances.

This system assists college authorities by limiting possibilities of misappropriation, improving accountability and having a record that cannot be tampered indicating all movements of funds. No transaction document stored in the blockchain can be changed, making it openly evident that any efforts to abuse or alter financial information will be identified quickly, which is why it is unnecessary to verify a transaction by any third party, and the control can be more robust. Moreover, the automated workflow process minimizes the number of human errors and slowness in general, which makes the financial management process more effective and reliable. The model consolidates institutional governance, boosts the level of trust among students, faculty, and auditors and the productivity of the college administrative activities is boosted.

The system can be further extended with the implementation of smart contracts and AI-based analytics to automatically approve budgets, forecast fund needs and enhance security even more in the future. This is going to require small-scale tests and suitable administrative policies before implementing this framework in larger educational networks.

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SMART ROUTE OPTIMIZATION FOR EMERGENCY VEHICLES USING MACHINE LEARNING

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ABSTRACT

Urban congestion significantly delays emergency response, directly affecting survival outcomes. This paper proposes a hybrid intelligent framework combining a CNN-LSTM traffic prediction model with a Deep Q-Network (DQN) routing agent to optimize emergency vehicle navigation in real time. The CNN component extracts spatial traffic features, while the LSTM captures temporal dependencies, enabling accurate short-term traffic forecasting. These predictions feed into a reinforcement learning-based routing agent that dynamically selects optimal paths under changing traffic conditions. Additionally, an IoT-enabled signal preemption module prioritizes emergency vehicles at intersections. The system is evaluated using SUMO simulations across three urban scenarios. Results show a 32–41% reduction in travel time and a 28% improvement in signal clearance efficiency compared to traditional shortest-path methods. The proposed framework demonstrates strong adaptability in dynamic environments and highlights the potential of AI-driven traffic systems for improving emergency response efficiency.

Keywords: *Emergency vehicle routing, CNN-LSTM, Deep Q-Network, intelligent transportation systems, traffic prediction, reinforcement learning, smart traffic signals, IoT traffic monitoring, adaptive routing*

I. INTRODUCTION

Rapid urbanization has intensified traffic congestion, particularly in developing cities. Emergency vehicles such as ambulances and fire trucks are often delayed due to unpredictable traffic conditions. Traditional routing methods rely on static shortest-path algorithms, which fail to adapt to real-time congestion dynamics. Recent advances in intelligent transportation systems emphasize the importance of spatiotemporal traffic modeling and adaptive decision-making. However, most systems treat prediction and routing independently, limiting their effectiveness in dynamic scenarios.

This paper proposes a unified framework that integrates:

- CNN-LSTM for traffic prediction
- DQN-based adaptive routing
- IoT-enabled signal preemption

The goal is to minimize emergency response time by enabling proactive and reactive traffic management.

II. LITERATURE REVIEW

1. Hybrid CNN-LSTM Models (2025) Studies show CNN-LSTM architectures outperform standalone models by capturing spatial and temporal traffic patterns effectively.
2. Attention-Based CNN-LSTM (2025) Enhanced models integrate attention mechanisms to improve prediction accuracy under noisy traffic conditions.
3. Deep Learning Traffic Systems (2025) Comparative analyses confirm LSTM-based hybrids achieve superior performance in real-time traffic forecasting.
4. Ambulance Routing with Deep Learning (2025) Multimodal systems combining CNN and LSTM achieve up to 99% detection accuracy and improve emergency response reliability.
5. Reinforcement Learning for Routing (2026) DQN and PPO-based routing systems adapt effectively to dynamic environments, outperforming static algorithms.
6. RL with Traffic Simulation (2026) Integration of CNN with RL in SUMO environments demonstrates improved route optimization and decision-making.

Despite recent advancements, there remains a notable gap in the development of unified architectures that seamlessly integrate traffic prediction, dynamic routing and signal control for efficient emergency vehicle management.

III. SYSTEM ARCHITECTURE & METHODOLOGY

The system begins with the data acquisition layer, where real-time information is collected from traffic cameras, GPS devices, road sensors and weather sources. This data is transmitted through a high-speed communication network such as 5G or IoT-based V2X systems. The traffic prediction module then processes the data using a CNN-LSTM model to forecast near-future traffic conditions by capturing spatial and temporal patterns. Based on these predictions, the DQN routing agent dynamically selects the most efficient route for the emergency vehicle. Simultaneously, the signal preemption module detects the approaching vehicle and overrides traffic signals to ensure a clear path at intersections. The system then provides the optimized route as output, minimizing travel time and delays. Finally, a feedback loop continuously updates the model using new data, improving overall system performance over time.

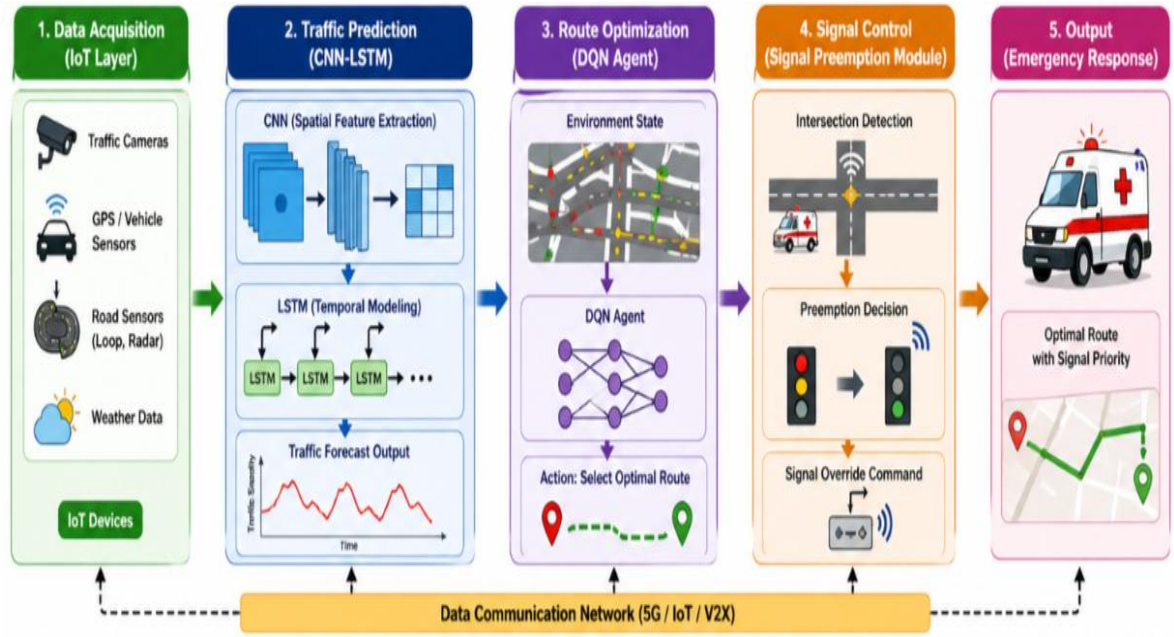

Figure 1: Overall System Architecture

CNN-LSTM Model

The CNN-LSTM model plays a crucial role in traffic prediction by combining spatial and temporal analysis. The Convolutional Neural Network (CNN) first extracts spatial features from traffic data such as road density patterns and congestion zones across different regions. These extracted features are then passed to the Long Short-Term Memory (LSTM) network, which models the temporal evolution of traffic by learning how traffic conditions change over time. By integrating both spatial and temporal insights, the model generates an output in the form of a predicted traffic state for the next time interval enabling proactive and informed decision-making for route optimization.

DQN Routing Agent

The routing problem is modelled as a Markov Decision Process (MDP), where the system continuously interacts with the traffic environment to make optimal decisions. In this framework, the state represents the current traffic conditions, including traffic density and the location of the emergency vehicle. Based on this state, the system takes an action, which involves selecting the most suitable route. After taking an action, the system receives a reward, designed to encourage minimized travel time and reduced congestion. By learning from these rewards over time, the model improves its ability to choose efficient routes in dynamic traffic scenarios.

Signal Preemption Module

The signal preemption module uses IoT-enabled traffic lights to manage intersections intelligently. When an emergency vehicle approaches, the system detects its presence and automatically overrides the normal traffic signal operation. This allows the signal to turn green along the vehicle's path, ensuring smooth passage. As a result, waiting time at intersections is significantly reduced, helping the emergency vehicle reach its destination faster.

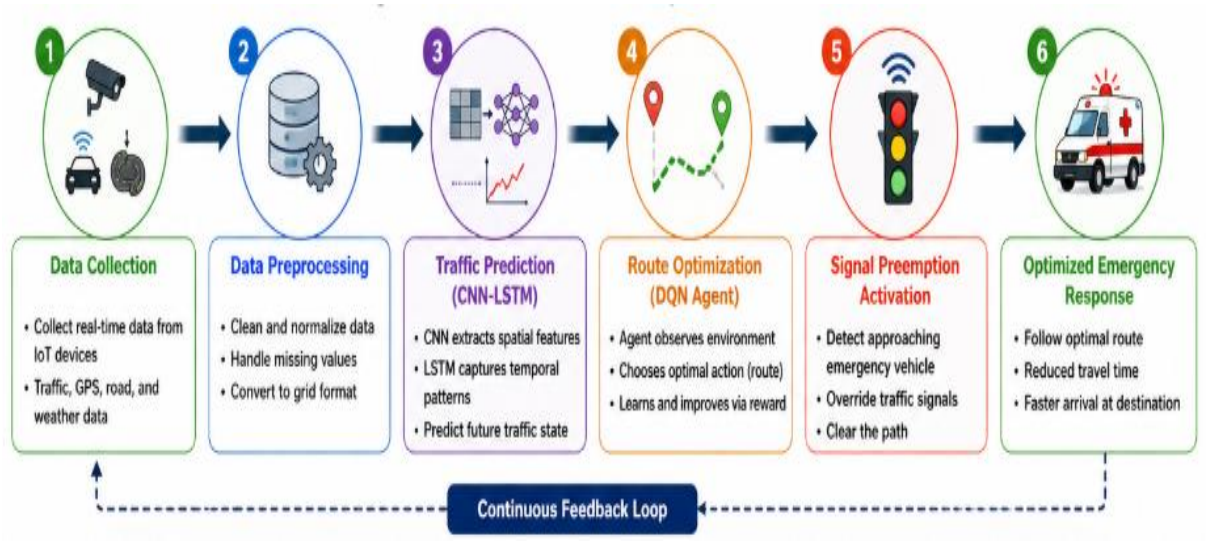

Figure 2: Workflow of proposed framework

The workflow begins with data collection, where real-time traffic information is gathered from IoT devices such as cameras, GPS systems and road sensors. This raw data is then passed to the data preprocessing stage, where it is cleaned, normalized and structured for analysis. Next, in the traffic prediction phase, a CNN-LSTM model analyzes the processed data to forecast short-term traffic conditions by capturing both spatial and temporal patterns. These predictions are fed into the route optimization stage, where a DQN-based agent evaluates possible paths and selects the optimal route that minimizes travel time.

The signal preemption stage is activated, allowing traffic signals along the selected route to be controlled dynamically, giving priority to the emergency vehicle by reducing stops at intersections. Finally, the system produces the optimized emergency response, where the vehicle follows the suggested route with minimal delay, while a continuous feedback loop updates the system to improve future predictions and decisions.

IV. EXPERIMENTAL SETUP & DATASET

The simulation environment for this study is developed using SUMO (Simulation of Urban Mobility), an open-source, highly portable traffic simulation platform widely used for modeling and analyzing intelligent transportation systems. To evaluate the robustness and adaptability of the proposed framework, experiments are conducted across three distinct city models. The first is a grid-based urban network, representing well-structured city layouts with uniform intersections and predictable traffic patterns. The second is a dense metropolitan layout, characterized by high traffic volume, complex road structures and frequent congestion, simulating conditions similar to large urban centers. The third model is a semi-urban mixed traffic environment, which reflects irregular road networks and heterogeneous traffic behavior commonly observed in smaller cities. These diverse scenarios ensure comprehensive testing of the system under varying traffic conditions and infrastructure complexities.

Parameter	City A	City B	City C
Road Length (km)	25	40	18

Intersections	60	120	45
Vehicles/hour	2000	5000	1500
Emergency Events	50	80	30

Table 1: Dataset Summary

V. RESULTS & DISCUSSION

The performance comparison of different routing algorithms highlights the effectiveness of the proposed approach. Traditional algorithms such as Dijkstra show low travel time reduction, as they rely on static conditions and achieve an accuracy of around 65%. Similarly, the A* algorithm performs moderately better, offering some improvement in travel time and limited adaptability to changing traffic conditions, with an accuracy of approximately 72%. In contrast, the proposed CNN-LSTM combined with the DQN model demonstrates significantly superior performance, achieving high travel time reduction and dynamic adaptability to real-time traffic scenarios. This approach attains an accuracy of 89%, clearly indicating its advantage in handling complex and evolving traffic environments for emergency vehicle routing.

Algorithm	Travel Time Reduction	Adaptability	Accuracy
Dijkstra	Low	Static	65%
A*	Moderate	Limited	72%
CNN - LSTM + DQN	High	Dynamic	89%

Table 2: Algorithm Comparison

The performance metrics clearly demonstrate the effectiveness of the proposed system when compared to the baseline scenario. The average travel time is significantly reduced from 18.5 minutes to 11.2 minutes, indicating faster emergency response. Similarly, the signal wait time at intersections decreases from 120 seconds to 65 seconds due to the implementation of signal preemption. In addition, route efficiency improves substantially from 68% to 92%, reflecting better path selection and traffic handling. These improvements highlight the system's ability to optimize routing and minimize delays in real-time traffic conditions.

VI. CONCLUSION

This paper presented a hybrid AI-based framework for optimizing emergency vehicle routing using CNN-LSTM and DQN models. By combining traffic prediction with adaptive decision-making, the system addresses the limitations of traditional routing methods. The integration of IoT-enabled signal preemption further enhances performance by reducing delays at intersections. Experimental results from SUMO simulations demonstrate significant improvements in travel time, route efficiency and adaptability under dynamic conditions. The proposed framework highlights the importance of unified intelligent systems that combine prediction, control and optimization. While challenges remain in real-world deployment and scalability, the approach provides a strong foundation for future smart city traffic systems. Ultimately, this research contributes toward reducing emergency response times and improving urban mobility through advanced AI-driven solutions.

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Title: Impact of Green Accounting Adoption in the Indian Economy for Environmental Sustainability

Abstract

In India, the intersection of green accounting and environmental sustainability is gaining importance due to rapid industrialisation and escalating ecological challenges such as resource depletion, pollution, and climate change. This paper examines the concept, theoretical underpinnings, policy landscape, challenges, and emerging opportunities associated with green accounting in the Indian context. Drawing on peer-reviewed empirical studies, institutional reports, and global sustainability. The findings indicate that while India has taken meaningful policy strides through the National Action Plan on Climate Change (NAPCC) and Corporate Social Responsibility (CSR) mandates, significant barriers—including inadequate standardisation, regulatory enforcement gaps, and corporate resistance—continue to impede effective green accounting adoption. Technological interventions such as artificial intelligence (AI) and blockchain, along with reinforced regulatory frameworks, are identified as transformative levers. Insights from this analysis are expected to guide future research and policy efforts to enhance environmental sustainability in the Indian economy.

Keywords: Green Accounting, Environmental Sustainability, Indian Economy, SEEA, Corporate Social Responsibility, Environmental Reporting, Sustainable Development

1. Introduction

Environmental sustainability has emerged as one of the most critical challenges confronting developing economies in the twenty-first century. India, one of the world's fastest-growing economies, faces a dual imperative: maintaining its industrial growth trajectory while simultaneously addressing severe ecological degradation. Rapid urbanisation, intensive resource extraction, and expanding manufacturing sectors have collectively intensified carbon emissions, freshwater scarcity, deforestation, and biodiversity loss (World Bank, 2023

Green accounting quantifies the environmental costs of economic activities and integrates them into national income accounts and corporate financial statements, enabling governments, regulators, and corporations to make decisions that internalise environmental externalities (Costanza et al., 2014). The conceptual origins of green accounting trace back to Peskin (1981) and the pioneering work of El Serafy (1989) on natural capital depreciation, which challenged the adequacy of conventional GDP as a measure of national welfare. Subsequently, the United Nations (UN) developed the System of Environmental-Economic Accounting (SEEA) as a global statistical standard for integrating environmental data with economic accounts (United Nations, 2021).

For India specifically, the relevance of green accounting is underscored by several empirical realities. The country ranks third globally in absolute greenhouse gas emissions and faces significant costs associated with air and water pollution, estimated at approximately 8.5% of GDP annually (World Bank, 2023). Despite progressive legislation such as the Environment (Protection) Act 1986, the Water (Prevention and Control of Pollution) Act 1974, and sector-specific environmental regulations, systematic integration of environmental costs into accounting and reporting frameworks remains nascent (Ministry of Environment, Forest and Climate Change [MoEFCC], 2022).

This paper aims to conduct a comprehensive review of the literature on green accounting in the Indian context, examine relevant theoretical frameworks and global standards, critically evaluate existing policy initiatives and implementation challenges, and identify future research and policy directions. The structure of the paper is as follows: Section 2 provides a detailed conceptual and theoretical treatment of

green accounting; Section 3 situates green accounting within India's policy landscape; Section 4 examines implementation challenges; Section 5 explores emerging opportunities; and Section 6 presents the conclusion with policy recommendations.

1.1 Significance of the Study

The importance of this study is to addresses a research gap in the Indian context where longitudinal, policy-oriented reviews of green accounting literature are limited (Rajput & Gupta, 2020; Sinha & Sharma, 2022). And it provides actionable insights for policymakers, corporate boards, and academic researchers at a time when India's Nationally Determined Contributions (NDCs) under the Paris Agreement demand accelerated sustainability action. It also contributes to the global discourse on the role of accounting systems in achieving the United Nations Sustainable Development Goals (SDGs), particularly SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action), and SDG 15 (Life on Land).

2. Concepts and Theoretical Foundations

2.1 Natural Capital Theory

Natural capital theory, advanced by Daly and Cobb (1989) and subsequently operationalised by Costanza and Daly (1992), holds that the stock of natural resources and ecosystem services constitutes productive capital analogous to manufactured and human capital. Sustainable economic growth requires maintaining—rather than depleting—this natural capital stock. Green accounting mechanisms, particularly natural resource accounting, provide the measurement tools to operationalise this principle within national and corporate accounting systems.

2.2 Stakeholder Theory

Freeman's (1984) stakeholder theory provides a normative foundation for corporate green accounting by arguing that firms are accountable not merely to shareholders but to a broader set of stakeholders—including communities, employees, governments, and future generations—whose interests are materially affected by corporate environmental conduct. This framework justifies voluntary and mandatory environmental disclosures as mechanisms for stakeholder accountability and corporate legitimacy (Gray et al., 2014).

2.3 Institutional Theory

DiMaggio and Powell (1983) articulate that organisations conform to institutional pressures—coercive, normative, and mimetic—in shaping their practices. Applied to green accounting, this means that regulatory mandates (coercive), professional accounting standards (normative), and peer benchmarking (mimetic) collectively drive firms to adopt environmental reporting practices, even in the absence of direct economic incentives (Suchman, 1995; Deegan, 2002).

3. Green Accounting in the Indian Policy Context

3.1 Evolution of Environmental Policy in India

India's environmental regulatory architecture has evolved substantially over five decades. The constitutional amendments of 1976 (Articles 48A and 51A(g)) enshrined environmental protection as a fundamental duty and directive principle of state policy (Government of India, 1976). Subsequent legislative milestones—including the Wildlife Protection Act 1972, the Water Act 1974, the Air Act 1981, the Environment (Protection) Act 1986, and the Forest Rights Act 2006—established a comprehensive, though uneven, regulatory framework for environmental governance (MoEFCC, 2022).

The NAPCC represents India's most comprehensive policy attempt to integrate sustainability into economic planning, though critics note that implementation gaps remain wide (Dubash, 2012; Khosla & Bhardwaj, 2019).

3.2 Corporate Sustainability Reporting Mandates

3.2.1 Companies Act 2013 and CSR Provisions

Section 135 of the Companies Act 2013 mandates Corporate Social Responsibility (CSR) spending for companies meeting specified financial thresholds. Companies with net worth of INR 500 crore or more, turnover of INR 1,000 crore or more, or net profit of INR 5 crore or more are required to spend at least 2% of their average net profit over the preceding three years on CSR activities, which may include environmental conservation (Ministry of Corporate Affairs [MCA], 2013). While CSR provisions have channelled significant resources toward environmental programmes, scholars note that environmental CSR disclosures remain qualitative and lack the precision of green accounting metrics (Mohan & Singh, 2017).

3.2.2 SEBI's Business Responsibility and Sustainability Report (BRSR)

The Securities and Exchange Board of India (SEBI) in 2021 introduced the Business Responsibility and Sustainability Report (BRSR) as a mandatory disclosure framework for the top 1,000 listed entities by market capitalisation, effective from FY2022–23 (SEBI, 2021). The BRSR, aligned with GRI Standards and the UN SDGs, requires companies to disclose quantitative data on greenhouse gas emissions, energy consumption, water withdrawal and consumption, waste generation, and supply chain sustainability. It represents a significant step toward standardised green accounting in India's corporate sector (Agarwal & Jain, 2023).

3.2.3 Environmental Impact Assessment (EIA)

The Environmental Impact Assessment Notification 2006 (revised draft 2020) requires project proponents to conduct comprehensive EIAs before undertaking new developmental projects. The EIA process mandates assessment of air, water, soil, biological, and socio-economic impacts, generating environmental cost data relevant to green accounting (MoEFCC, 2020). However, weaknesses in EIA quality, public consultation processes, and post-approval monitoring have diminished its effectiveness as a green accounting instrument (Narain, 2019; Paliwal, 2006).

3.3 National Statistical Initiatives

The Ministry of Statistics and Programme Implementation (MoSPI) has undertaken efforts to develop India's System of National Accounts in alignment with the SEEA framework. The Green National Accounts initiative, drawing on the work of the Expert Group chaired by Sir Partha Dasgupta, has piloted natural resource accounting across several states and natural capital categories including forests, water, land, minerals, and fisheries (Dasgupta, 2021; MoSPI, 2023). Despite these efforts, a comprehensive, institutionalised system of green national accounts has yet to be fully operationalised in India.

4. Challenges in Implementing Green Accounting in India

4.1 Absence of Standardised Reporting Frameworks

A major barrier to green accounting in India is the lack of uniform, sector-specific standards. While BRSR and GRI have improved disclosures among large firms, SMEs remain largely excluded. This leads to inconsistent reporting, limiting comparability and usefulness of environmental data.

4.2 Difficulties in Quantifying Environmental Costs

Measuring environmental costs is complex due to challenges in valuing factors like biodiversity loss and climate risks. Methods such as contingent valuation require significant expertise and data, which are often lacking in India, making accurate environmental accounting difficult.

4.3 Corporate Resistance and Short-Termism

Many firms view green accounting as a compliance burden rather than a strategic tool. Short-term financial goals dominate decision-making, limiting sustainability efforts, though rising ESG focus is gradually influencing corporate behavior.

4.4 Regulatory Enforcement Gaps

Despite strong environmental laws, weak enforcement—due to understaffing, weak penalties, and regulatory delays—reduces effectiveness. Fragmented governance between central and state authorities further complicates implementation.

4.5 Limited Awareness and Capacity

Green accounting requires specialised skills that are not widely developed in India. Limited professional training and low public awareness hinder its adoption and effective implementation.

5. Emerging Opportunities for Green Accounting in India

5.1. Artificial Intelligence and Big Data: AI and big data improve environmental reporting through real-time data collection using remote sensing, satellites, and IoT. They enhance accuracy, enable predictive analysis, and reduce compliance costs.
5.2 Blockchain for Environmental Accountability: Blockchain ensures secure and transparent environmental data by creating tamper-proof records, reducing risks of manipulation and greenwashing.
5.3 Green Finance and Investment Incentives: India's growing green finance market, including green bonds and sustainability-linked loans, encourages firms to adopt green accounting. RBI policies further support climate-related disclosures.
5.4 Alignment with India's NDCs and Net-Zero Commitments: India's climate targets require strong green accounting systems to monitor and verify progress, making it a key policy driver.
5.5 Academic and Professional Capacity Building: UGC, ICAI, and ICMAI are promoting environmental accounting education. Expanding training and research will support wider adoption.

6. Conclusion and Policy Recommendations

6.1 Summary of Findings

Green accounting is essential for translating India's sustainability goals into measurable outcomes. Despite progress through policies like NAPCC and BRSR, a significant gap remains between policy and practice. Key challenges include lack of standardisation, measurement issues, weak enforcement, corporate short-termism, and limited expertise.

6.2 Policy Recommendations

Based on the foregoing analysis, the following policy recommendations are advanced:

1. **Standardisation:** Develop tiered, sector-specific environmental accounting standards, including SMEs.
2. **Natural Capital Accounting:** Strengthen SEEA-based national accounts and introduce Green GDP.
3. **Regulatory Framework:** Establish a dedicated environmental reporting regulator.
4. **Technology Use:** Invest in data infrastructure like IoT and satellite monitoring.
5. **Capacity Building:** Expand environmental accounting education and professional training.
6. **Incentives:** Provide tax benefits and financial incentives for adopting green accounting.

6.3 Future Research Directions

Longitudinal studies examining the financial performance implications of green accounting adoption among Indian listed companies would contribute to the business case literature sector-level analyses of natural capital valuation methodologies—particularly for water-intensive industries and forest-based supply chains—are needed to develop operationally workable green accounting standards for India's specific ecological context.

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An AI-Based Crisis Tweet Analytics Platform for Resource Demand Prediction in Natural Disasters

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ABSTRACT

Natural disasters such as floods, earthquakes, cyclones, and wildfires severely impact human life and infrastructure, while effective management is hindered by rapid escalation, communication failures, and massive unstructured digital data. Existing systems depend on manual reporting and delayed field updates, resulting in poor situational awareness, slow response, inefficient resource allocation, and weak coordination among authorities, NGOs, and rescue teams. To address these challenges, this project proposes a scalable API-driven smart disaster response system with a real-time dashboard that automatically collects and analyzes geo-tagged crisis data from multiple social media platforms to support rapid and informed decision-making. The proposed system employs BERT-based natural language processing to analyze social media content and accurately identify disaster types, urgency levels, and specific requirements such as rescue, medical assistance, food, water, and shelter. Spatial clustering of affected regions is performed using the DBSCAN algorithm, enabling the detection of disaster hotspots and severely impacted zones without requiring predefined regional boundaries. Furthermore, a Graph Neural Network (GNN) is utilized to model spatial relationships between nearby affected areas and to predict location-wise priority resource demands. The system is exposed as a secure RESTful API that continuously updates a web-based dashboard with live analytics, demand maps, and priority rankings of affected locations. Based on the predicted requirements, automated alerts and structured reports are generated and transmitted to government authorities, non-governmental organizations, and rescue teams to facilitate optimal resource allocation and rapid emergency response.

I. INTRODUCTION

Natural disasters such as earthquakes, floods, cyclones, landslides, and wildfires cause severe damage to human life, infrastructure, and the environment. These events often disrupt communication networks and create urgent demand for rescue teams, food, water, shelter, and medical support. During emergency situations, obtaining timely and accurate information about affected locations remains a major challenge for disaster management authorities.

In recent years, social media platforms have emerged as important sources of real-time crisis information. During disasters, people share messages, images, geolocation details, and requests for help through platforms such as Twitter and other social networks. However, the massive volume, informal language, and unstructured nature of social media data make manual analysis difficult and time-consuming. Critical rescue information may be missed without intelligent automated analysis.

To address these challenges, **CrisisSenseAPI** is proposed as an AI-based crisis tweet analytics platform that automatically collects and analyzes disaster-related social media data. The system employs BERT-based natural language processing to identify disaster type and urgency, DBSCAN clustering to detect disaster hotspots, and Graph Neural Networks to predict location-wise resource demands. A real-time dashboard, automated alerts, and structured reports support government authorities, NGOs, and rescue teams in making faster, data-driven decisions for effective disaster response.

II. PROBLEM STATEMENT

Natural disasters such as floods, earthquakes, cyclones, and wildfires cause significant damage to human life, infrastructure, and the environment. During such events, obtaining timely and accurate information about affected areas and the needs of people becomes a major challenge for disaster management authorities. Traditional disaster response systems rely mainly on manual reports, field surveys, and official communication channels, which often take considerable time to collect and analyze. As a result, emergency response teams may face delays in identifying critical situations and allocating resources effectively. In recent years, social media platforms have become an important source of real-time information during disasters. People frequently share messages, images, and location details about their situations, requests for help, and updates on disaster conditions. However, the large volume of unstructured data generated on these platforms makes it difficult to manually analyze and extract useful insights. Important information may be overlooked due to the rapid flow of posts, irrelevant content, and lack of proper filtering mechanisms. Another major problem is the difficulty in identifying disaster hotspots and understanding the urgency of different situations. Without proper analysis tools, it is challenging for authorities to determine which locations require immediate attention and what types of resources are needed. This often leads to inefficient resource distribution, where some affected regions receive insufficient support while others may receive more resources than required. Therefore, there is a need for an intelligent system that can automatically analyze social media data, identify disaster-related posts, detect affected locations, and predict resource requirements. Such a system can help authorities gain real-time situational awareness and support faster decision-making during emergency situations. By utilizing advanced technologies such as natural language processing and machine learning, the proposed system aims to transform large volumes of social media data into meaningful insights that improve disaster monitoring and response efficiency.

III. EXISTING SYSTEMS AND LIMITATIONS

- **Manual Field Surveys and Reports**

In traditional disaster management, information about affected areas and victims is mainly collected through field officers, volunteers, and local authorities. These reports are often delayed due to damaged infrastructure, blocked transportation, and limited communication facilities, which slows down decision-making and emergency response.

- **Emergency Call Centers and Control Rooms**

Control rooms and helpline numbers are used to receive distress calls from the public. However, during large-scale disasters, call centers become overloaded, many calls remain unanswered, and critical information is missed or recorded incompletely.

- **Media-Based Situation Assessment**

Authorities rely on television news, radio broadcasts, and newspapers to understand disaster severity. These sources provide only high-level information and lack precise, location-specific details about real-time resource needs.

- **Centralized Government Databases**

Existing systems store disaster data in centralized databases that are updated manually. These systems do not support real-time analytics or predictive modeling, making it difficult to anticipate future demands or prioritize regions effectively.

- **Experience-Based Resource Allocation**

Relief materials such as food, water, and medical supplies are distributed based on past experience or rough estimates rather than actual real-time demand. This often results in shortages in severely affected areas and wastage in less affected regions.

IV. PROPOSED SYSTEM:

The proposed system is an intelligent disaster response platform that analyzes social media data to detect crisis situations, identify affected regions, and predict resource requirements in real time. It integrates advanced machine learning algorithms to process unstructured social media posts and generate actionable insights for government authorities, NGOs, and rescue teams to respond quickly during disaster events.

A. Crisis Analysis Using BERT (CrisisNet)

In this stage, social media posts are collected and processed using the BERT-based CrisisNet model. The algorithm analyzes the textual content of tweets and other posts to identify disaster type, urgency level, and required resources such as rescue teams, food, water, or medical aid. This enables the system to convert unstructured social media text into meaningful crisis information. Additionally, the BERT model captures contextual relationships between words using transformer-based attention mechanisms, improving the accuracy of disaster detection. It also supports real-time analysis of large volumes of social media data to quickly identify emerging crisis situations.

B. Disaster Hotspot Detection Using DBSCAN

After identifying crisis-related posts, the DBSCAN clustering algorithm is applied to geo-tagged data to detect disaster hotspots. This algorithm groups nearby crisis posts based on geographical proximity and identifies regions with a high concentration of disaster activity. These clusters represent affected areas that require immediate attention.

Furthermore, DBSCAN automatically separates noise or irrelevant data points from meaningful clusters, improving hotspot detection accuracy. This allows the system to identify the most severely affected locations without requiring predefined cluster numbers.

C. Resource Demand Prediction Using GNN (DemandNet)

Once disaster hotspots are identified, the DemandNet model based on Graph Neural Networks analyzes the relationships between affected regions. It predicts location-wise priority resource requirements by considering factors such as the number of crisis posts, urgency levels, and spatial connections between regions. The model represents each hotspot as a node and nearby locations as edges within a spatial graph. Through message passing between nodes, the system learns demand patterns and estimates the required resources for each affected region.

D. Alert and Response Generation

Based on the predicted resource demands and disaster severity, the system generates automated alerts and notifications for government authorities, NGOs, and rescue teams. The platform also provides a real-time dashboard that visualizes disaster hotspots and resource needs, enabling faster decision-making and coordinated disaster response operations. In addition, alerts include structured information such as disaster location, urgency level, and recommended resources to assist emergency responders. This ensures timely communication and effective coordination among different disaster management agencies.

V. ALGORITHM USED

1.BERT (CrisisNet) – Crisis Tweet Classification

BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based natural language processing model designed to understand the contextual meaning of text. It processes text in both forward and backward directions to capture relationships between words. This allows the model to understand the intent and semantics of social media messages. In disaster analysis, BERT is used to classify tweets into disaster-related categories and identify urgency levels and resource requirements.

Algorithm Workflow

1. Collect social media text data from APIs or datasets.
2. Preprocess the text by removing noise and irrelevant characters.
3. Tokenize the text and convert it into embeddings using BERT.
4. Pass embeddings through the BERT classification layer.
5. Predict disaster type, urgency level, and required resources.

2. DBSCAN – Disaster Hotspot Detection

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a clustering algorithm that groups data points based on density. It identifies clusters where many points exist within a specified distance and separates noise points that do not belong to any cluster. This algorithm is useful for spatial data analysis because it does not require predefined cluster numbers. In disaster analysis, DBSCAN is used to detect regions with a high concentration of crisis-related posts.

Algorithm Workflow

1. Receive geo-tagged crisis posts from the classification module.
2. Define parameters such as epsilon distance and minimum points.
3. Identify neighboring data points within the specified distance.
4. Group dense regions into clusters.
5. Mark isolated points as noise.
6. Output clusters representing disaster hotspots.

3. Graph Neural Network (DemandNet) – Resource Demand Prediction

Graph Neural Networks are deep learning models designed to analyze graph-structured data. In this approach, nodes represent entities and edges represent relationships between them. The model learns patterns by exchanging information between connected nodes through message passing. In disaster analysis, each hotspot is represented as a node in a spatial graph. The GNN model predicts the resource requirements of each region based on neighboring hotspots.

Algorithm Workflow

1. Receive disaster hotspots detected by DBSCAN.
2. Represent each hotspot as a node in a graph.
3. Connect nearby hotspots using edges.
4. Extract features such as urgency level and number of posts.
5. Apply graph neural network layers to aggregate node information.
6. Predict location-wise resource demand.

VI. TECHNOLOGIES USED

The CrisisSenseAPI system is built using a carefully selected technology stack to ensure efficiency, scalability, and real-time disaster response support.

Frontend: HTML, CSS, JavaScript, and Bootstrap are used to create a responsive and user-friendly dashboard interface that allows authorities, NGOs, rescue teams, and citizens to monitor disaster hotspots, resource demands, alerts, and contribution updates smoothly.

Backend: Python with the Flask framework is used to handle application logic, process crisis data, manage RESTful API requests, and integrate different machine learning modules. Flask enables lightweight and efficient backend development for real-time disaster monitoring.

Database: MySQL is used as the relational database to store social media crisis posts, hotspot cluster information, resource demand predictions, user details, alert logs, and contribution records in a structured and secure manner.

AI & Machine Learning: BERT-based natural language processing is used to classify disaster type, urgency level, and required resources from crisis tweets. DBSCAN clustering is used to detect disaster hotspots from geo-tagged data. Graph Neural Networks (DemandNet) are used to model spatial relationships and predict location-wise priority resource demands. NumPy and Pandas support data preprocessing and feature analysis.

Visualization & Alerts: Matplotlib, Plotly/Dash, and mapping tools are used for visualizing hotspot locations, urgency graphs, and demand maps through a real-time dashboard. SMTP and SMS notification services are used for generating automated alerts and structured reports for emergency responders.

Development Tools: Visual Studio Code (VS Code) is used as the primary development environment. Tools such as Postman are used for testing API endpoints, and the system is developed and tested on Windows operating system.

VII. EXPECTED OUTCOMES

The CrisisSenseAPI system is expected to deliver significant benefits in both disaster response efficiency and technological advancement.

Disaster Response Efficiency: The system will automate the analysis of crisis-related social media data, reducing manual effort and significantly improving response time during emergency situations. This enables faster identification of affected regions and supports rapid disaster response operations.

Accuracy and Resource Prioritization: By automatically classifying disaster posts, detecting hotspots, and predicting resource demands, the system minimizes human error and improves the accuracy of relief planning. This ensures that critical resources such as food, water, shelter, and medical aid are allocated where they are most needed.

Improved Coordination: Government authorities, NGOs, and rescue teams can use real-time dashboards, alerts, and structured reports to improve coordination and decision-making. This reduces communication gaps and strengthens collaborative emergency response.

User Experience: The system provides a user-friendly dashboard with hotspot maps, urgency indicators, and analytical visualizations, allowing users to monitor disaster situations and respond effectively. Citizens can also receive updates and contribute resources through the platform.

Technical Contribution: The project demonstrates the practical integration of natural language processing, clustering algorithms, graph neural networks, and web technologies into a unified disaster management platform. It establishes a foundation for future advancements in AI-assisted emergency response systems.

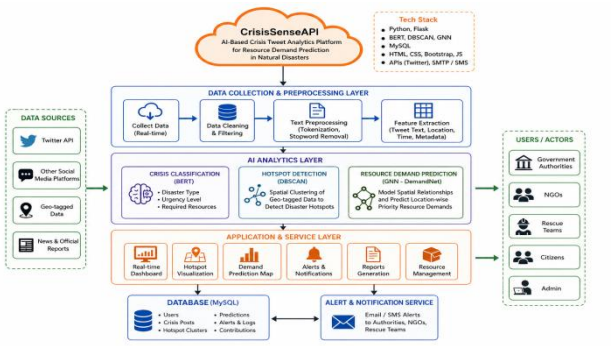
VIII. SYSTEM DESIGN OVERVIEW

The architectural design of **CrisisSenseAPI** follows a modular and layered approach, ensuring clear separation of concerns across different components of the system. The web-based frontend, developed using HTML, CSS, Bootstrap, and JavaScript, communicates with the Flask backend through HTTP requests and RESTful API endpoints. The backend processes social media data, manages application logic, and coordinates with BERT-based crisis classification, DBSCAN hotspot detection, and GNN-based resource demand prediction modules. The MySQL database is used to store user data, crisis posts, hotspot details, prediction results, alerts, and contribution records, ensuring efficient data management.

The use case model of CrisisSenseAPI involves multiple actors such as Government Authority, NGO, Rescue Team, Citizen, and Admin. These users interact with the system to perform operations such as registration, login, crisis data monitoring, hotspot visualization, resource demand analysis, alert viewing, contribution management, and report generation. The system handles all processing tasks internally, including social media data collection, text preprocessing, disaster type classification, urgency detection, hotspot clustering, resource prediction, and automated alert generation, providing a seamless and intelligent disaster response workflow.

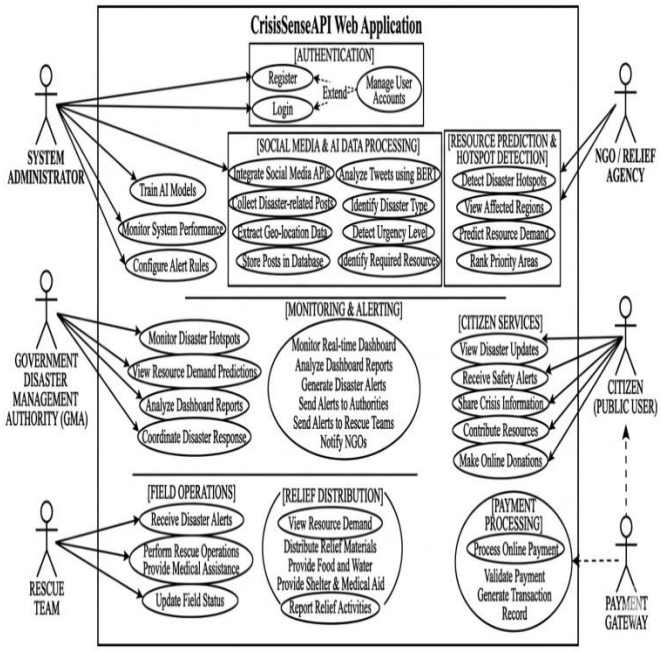
The system is designed with a modular structure, where each component such as data collection, preprocessing, crisis analysis, hotspot detection, demand prediction, dashboard visualization, and notification generation operates independently while remaining fully integrated. This modular design allows easy updates, scalability, and the addition of new features without affecting the existing functionality. It also simplifies maintenance and improves system reliability.

Security and data management are handled using standard practices, including user authentication, controlled access, and structured database storage. User information, disaster data, prediction results, and alert records are securely stored in the database, ensuring privacy and integrity. Overall, the system design provides a robust and scalable framework for AI-based disaster monitoring, resource demand prediction, and efficient emergency response.



IX. CONCLUSION

In conclusion, this project presents an intelligent system for analyzing disaster-related information from social media platforms to support effective disaster response and management. The system processes large volumes of social media data and identifies crisis-related messages using advanced data analysis techniques. Natural language processing is applied to understand the textual content of tweets and classify them based on disaster type, urgency level, and required resources. The system utilizes the **BERT-based model** for crisis tweet classification, which enables accurate understanding of contextual information in social media posts. The **DBSCAN clustering algorithm** is used to detect disaster hotspots by grouping geo-tagged posts based on geographical proximity. Furthermore, a **Graph Neural Network (GNN)** model is applied to analyze relationships between affected regions and predict location-wise resource demands. The analyzed results are visualized through a dashboard and automated alerts are generated to inform authorities, NGOs, and rescue teams about disaster situations and resource requirements. The experimental results show that the system effectively identifies disaster events and supports decision-making for emergency response. Overall, the project demonstrates how combining natural language processing, clustering techniques, and graph-based learning models can improve disaster monitoring, situational awareness, and resource allocation during crisis situations.



Use-Case Diagram

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A Review of Spectral Properties of Coprime Graphs for Dihedral Groups

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1. Abstract

This review examines a 2025 study by Romdhini, Abdurahim, and Maharani on the spectral properties of coprime graphs constructed from dihedral groups. A coprime graph connects group elements when their orders are coprime. The original paper focuses on the dihedral group D_n of order $2n$ under two specific conditions: when n is an odd prime power and when n is a power of two. In these cases, the coprime graph simplifies into either a complete tripartite graph or a complete bipartite graph. The authors derive characteristic polynomials for three fundamental matrices adjacency, Laplacian, and signless Laplacian and compute the spectral radius and graph energy for each. The findings classify these graphs as hypoenergetic or nonhypoenergetic and reveal a surprising coincidence between Laplacian and signless Laplacian spectra in the bipartite case. This review presents those results in plain language, focusing on concepts rather than algebraic details.

2. Introduction

Spectral graph theory studies graphs by examining the eigenvalues of matrices associated with them, such as the adjacency matrix or the Laplacian matrix. These eigenvalues reveal important properties of the graph, including connectivity, bipartiteness, and global energy. One rich source of interesting graphs is group theory: given any finite group, one can define a graph on the group elements based on some algebraic condition.

The coprime graph is one such construction. Two distinct group elements are adjacent if their orders (the smallest positive integers that bring the element to the identity) are coprime meaning they share no common prime factor. This seemingly simple rule produces graphs with elegant structures, especially for well-known groups like the dihedral group.

The dihedral group D_{2n} represents the symmetries of a regular n −gon, including rotations and reflections. Previous research established that the coprime graph of D_{2n} takes on a highly regular form depending on the arithmetic nature of nn. When n is an odd prime power, the graph becomes complete

tripartite (vertices split into three sets, with all cross-edges present). When n is a power of two, the graph becomes complete bipartite (vertices split into two sets, again with all cross-edges).

The original paper by Romdhini and colleagues builds on these structural results. Instead of merely describing the graph, they compute its spectral properties. They ask: What are the eigenvalues of the adjacency, Laplacian, and signless Laplacian matrices? What are the characteristic polynomials? How much energy does the graph contain? Answering these questions deepens our understanding of how algebraic structure translates into spectral behavior.

This review summarizes their work without reproducing dense mathematical derivations. The goal is to communicate the key ideas, results, and implications to a broader audience interested in graph theory or group theory

3. Basic Definitions

Before discussing the results, it is helpful to recall a few essential concepts.

Dihedral Group D_{2n}: This is the group of symmetries of a regular polygon with n sides. It contains $2n$ elements: n rotations (including the identity) and nn reflections. The group is non-abelian for $n \geq 3$, meaning the order of operations matters.

Order of an Element: In group theory, the order of an element is the smallest positive integer k such that raising the element to the k-th power gives the identity element. For example, the identity has order 1; a rotation by $360/n$ degrees has order n; a reflection always has order 2.

Coprime Graph $\Gamma(G)$:Given a finite group G, the coprime graph has vertex set G itself. Two distinct vertices u and v are connected by an edge if and only if the orders of u and v are coprime. This definition links number theory (coprimeness) with graph structure.

Complete Bipartite and Tripartite Graphs: A complete bipartite graph splits vertices into two groups, and every vertex in one group connects to every vertex in the other group (but no edges within the same group). A complete tripartite graph splits vertices into three groups, with all possible edges between different groups and no edges inside any group.

Adjacency Matrix :A square matrix where the entry in row i and column j is 1 if vertices i and j are adjacent, and 0 otherwise. The eigenvalues of this matrix form the adjacency spectrum.

Graph Energy: Introduced by Ivan Gutman in 1978, the energy of a graph is the sum of the absolute values of its adjacency eigenvalues. It originated in chemistry as a measure of the total $\pi\pi$-electron energy in conjugated hydrocarbons but has since become a standard graph invariant.

Spectral Radius: The largest absolute eigenvalue of a matrix. For the adjacency matrix, it correlates with the maximum degree and other structural properties.

Hypoenergetic and Nonhypoenergetic Graphs: A graph on m vertices is called hypoenergetic if its energy is less than mm; strongly hypoenergetic if energy is less than $m - 1$; and nonhypoenergetic if energy is at least mm. These classifications help compare graphs of the same size.

4. Concept and Key Findings

The original paper proceeds case by case, first analyzing the tripartite scenario (odd prime powers) and then the bipartite scenario (powers of two). In each case, the authors write down the adjacency, Laplacian, and signless Laplacian matrices in block form, then simplify the determinants using systematic row and column operations.

Tripartite Case (n odd prime power): Here, the vertex set naturally separates into three types: the identity element, the non-identity rotations (a_i), and the reflections. The identity connects to everyone, giving it degree $2n-1$. Each non-identity rotation connects to all reflections and the identity, but not to other rotations, yielding degree $n+1$. Each reflection connects to all rotations and the identity, but not to other reflections, yielding degree n.

The authors derive characteristic polynomials for all three matrices. These polynomials factor into products of linear terms and one or two small irreducible factors. This factorization reveals the eigenvalues explicitly. For instance, the Laplacian spectrum includes eigenvalues 0, n, $2n$ (twice), and n+1 with multiplicity n−2. The presence of repeated eigenvalues indicates high symmetry.

Bipartite Case (n=2k): This case is even simpler. The vertex set splits into two types: the identity alone versus all other elements (both rotations and reflections). The identity connects to everyone else. Every other element connects only to the identity not to each other because their orders are all even (rotations have order a power of two, reflections have order 2), so any two non-identity elements share a factor of 2. Thus, their orders are never coprime.

The graphs here are stars in disguise: a central vertex (the identity) connected to 2n−1 leaves. This is a complete bipartite graph. The spectral analysis becomes straightforward. The adjacency eigenvalues are 0 (with high multiplicity) and $\pm 2n-1$. The Laplacian eigenvalues are 0, 1 (many times), and $2n$. Remarkably, the signless Laplacian yields the exact same polynomial as the Laplacian—a coincidence the authors explicitly note as a corollary.

Energy Calculations: Using the eigenvalues, the authors compute the graph energy for each case. For the bipartite case (powers of two), the adjacency energy is 2$2n$−1. Since the number of vertices is $2n$, this energy is less than $2n$−1 for all $n \geq 2$, making the graph strongly hypoenergetic from the adjacency perspective. However, the Laplacian energy is 2($2n$−1), which exceeds $2n$, placing it in the nonhypoenergetic category.

The authors also observe that all computed energies are even integers (in the Laplacian case) and never odd, consistent with a known theorem by Bapat and Pati that graph energy cannot be an odd integer.

Broader Significance: This work connects three mathematical domains: group theory (dihedral groups), number theory (coprimeness conditions), and spectral graph theory (eigenvalues and energy). The clear separation into two arithmetic cases shows how the prime factorization of nn dramatically changes the

graph structure and its spectral properties. The coincidence of Laplacian and signless Laplacian spectra in the bipartite case is a subtle but important observation that may guide future research on other graph families.

5. Conclusion

The study by Romdhini and colleagues provides a complete spectral analysis of coprime graphs for dihedral groups under two natural arithmetic conditions. By exploiting the complete tripartite or bipartite structure of these graphs, they derive closed-form characteristic polynomials for the adjacency, Laplacian, and signless Laplacian matrices. From these polynomials, they extract eigenvalues, spectral radii, and graph energies. The results classify the graphs energetically and reveal a notable spectral coincidence in the bipartite case.

For readers interested in applying these results, the paper offers ready-to-use formulas. For theorists, it demonstrates how algebraic structure simplifies spectral calculations. Future work could extend this approach to other families of groups, such as symmetric groups, quaternion groups, or semidirect products. Additionally, the energy classifications could have implications in network science or chemical graph theory, where hypoenergetic graphs model certain molecular structures.

In summary, this research enriches the growing literature on graphs defined by group-theoretic conditions and provides a clear example of how spectral methods can be systematically applied.

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Consumer Preference in Multivendor E-Commerce Marketplaces: An Exploratory Perspective

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Abstract

E-Commerce Multivendor Marketplaces offer a variety of products to the consumer all sold on a single digital platform; while multivendor e-commerce marketplaces enhance accessibility, variety, and convenience, they also introduce significant complexity into the consumer decision-making process. The consumers often undergo heightened awareness, the benefits offered, many a times become a bane to completing the purchase. Consumers face issues such as information overload, quality validation, trust and most importantly the decision regarding vendor selection from among the many. For the sellers unless they understand and address these issues, acquiring and retention of customers looks grim. This paper brings to the fore an exploratory context regarding consumer preference in vendor selection when buying on e-commerce multivendor marketplaces.

Keywords: Consumer Behaviour Process, E-Commerce, Multivendor Marketplace, Consumer Preference, Consumer Behaviour Determinants

5. Introduction

5.1. Scaling Heights: The E-Commerce Sector

The internet heralded the ecommerce shopping movement, since the first online purchase in 1984 ecommerce has grown astronomically, the present growth rate since can be pegged at 400% in the timespan of 40 years. Figure 1 illustrates the growth of the e-commerce market; presently valued at $6.8 trillion, it is estimated to grow to $8 trillion by the year 2027 [1]. In comparison to some of the larger sectors such as oil and gas, and the manufacturing sector, e-commerce can be said to be an infant sector that has been on an accelerated growth trajectory[2]. The global economy is undergoing a transformation. Through the use of online technologies, all businesses are being transformed into information-based operations. The Internet has broadened the scope of businesses. E-commerce represents a paradigm shift that affects both marketers and customers [3]

As an industry that contributes significantly to the global GDP growth, ecommerce is a sector to reckon with. The consumers are the driving force in this sector and their behaviour dictates all decisions; right from the website design to the products sold on the website. Every plan made, very strategy implemented are all customer centric. E-commerce represents a rapidly growing share of consumer spending[4]. Therefore, it is not surprising that all the stakeholders in the e-commerce sector are committed to understanding the consumer behaviour process to serve them better[5].

5.2. Consumer Decision Making in Digital Environment

The consumer decision-making process consists of several stages that individuals experience when acquiring a product or service [6].The steps are no different from the traditional consumer decision making process. The stages are briefly described below:

- It starts with problem/need recognition – the consumer in this stage is faced with a problem or need that arose, which can be solved through the purchase of a particular product or service[7]
- The next stage is the consideration/information search – this is the stage where the consumers start their quest on search engines, they become information resources. The initial search is regarding availability products (what kind of products will satiate their needs), the consumers then at this stage become aware of brands that can satisfy their need[8].
- The following stage is the alternatives evaluation – this is the stage where comparative analysis takes place, which market places offer better choice in terms of product quality, price and services et al. All the alternatives are evaluated and usually the consumer zeroes in on a few items that have passed the evaluation criteria[9].
- The next stage is a crucial stage where they decide on the purchase – which brand to buy, when to buy, and from whom to buy. This is the stage where many external factors play a role in validating the consumers' final choice. The external factors that influence the consumers' decision are many

and a few are listed: trust on the e-merchant, e-word of mouth (e-wom), online reviews, influencer ratings etc.,[10,11].

- The next two stages are post purchase behaviour, the consumer having bought the product next evaluates the purchases' worth– is it's a purchase that adds value then the customer is satisfied as the product meets the customers' expectations, dissatisfaction results when the product purchased does not meet the customer expectations i.e., the product does not perform as expected[12,13].

5.3. Rise of Multivendor Marketplaces

A digital platform business can be defined as a two-sided market, which is an environment with supplier and consumer groups that engage in exchanges and transactions [14]. A multivendor marketplace can be thought of as a digital shopping mall, a single digital storefront that offers a plethora of products. It is can be described as an online platform where sellers can register, list and sell their products to consumers all from a single website. Consumers prefer shopping on multivendor websites, this preference can be attributed to the variety that these marketplaces offer along with the convenience of shopping that they offer. Inevitably all consumers tend to compare products in the competitive set, digital marketplaces have altogether eliminated this tedious task of visiting several stores before confirming a purchase. The ease of buying/ convenience is deemed an important reason for the rapid growth of multivendor digital marketplaces.

Multivendor marketplaces are categorised into types based on:

- Product Offerings – product based, services based or hybrid marketplaces
- Target Audience – B2B, B2C, C2C marketplaces
- Business Model – Horizontal marketplaces that offer a variety of products across different categories and Vertical marketplaces that sell products connected to a niche area.

The e-commerce marketplaces offer a win-win advantage to all the stakeholders; the consumers stand to gain benefits in terms of variety and convenience; the vendors gain access to larger customer base and less operational overheads costmeanwhile the platform administrators have the advantage of low inventory risk and scalability. Rather than competing with fixed assets and capabilities, such as a network of stores, the power of multi-sided marketplaces comes from their ability to tap into a large group of end-customers and providers [15].

6. Challenges in Multivendor Marketplaces

Multivendor marketplaces present a dual-edged ecosystem wherein consumers benefit from variety and competitive pricing, while simultaneously facing risks related to trust and quality inconsistency, and sellers encounter challenges such as intense competition, platform dependency, and constrained brand differentiation[16].

6.1. Seller Challenges:

The accessibility to multiple sellers, combined with the convenience of online shopping, represents one of the most significant advantages of multivendor marketplaces. However, this very characteristic—where numerous vendors offer similar or diverse product varieties—intensifies competition among sellers[17]. The online buying process is often marked by increased consumer awareness, with buyers comparing multiple vendors and even identifying alternative products to satisfy their needs.

At the same time, sellers become highly dependent on the platform, as algorithms and policies largely determine product visibility and reach. This dependency makes it difficult for sellers to build a distinct brand identity, especially since marketplaces tend to promote the platform rather than individual brands. Additionally, the requirement to pay commissions and invest in advertising further reduces profit margins. Operational challenges such as logistics and inventory management add to the complexity of selling in such environments.

Reviews, which serve as a critical trust-building cue for consumers, also present challenges, as their authenticity and impact can significantly influence seller performance. Unless these issues are effectively addressed, they may hinder both seller success and the overall buying process within multivendor marketplaces.

6.2. Consumer Challenges:

While multivendor marketplaces offer convenience and variety, they also present challenges that can hinder the completion of the buying process. While online shopping offers convenience, it removes the opportunity for tangible product evaluation, thereby shifting consumer reliance to seller cues for trust formation and variety may increase the likelihood of finding products that meet consumer needs, excessive options can lead to information overload and make decision-making more difficult. The absence of physical inspection in online marketplaces makes it difficult for consumers to accurately assess product quality, thereby acting as a significant constraint in the buying process. A commonly cited reason for product returns is the mismatch between the received product and its online representation, as descriptions and images may sometimes be misleading. This challenge is further intensified in multivendor environments where multiple sellers offer similar products, making quality validation even more complex. Although return policies partially mitigate this issue, they are not always consumer-friendly and may vary across sellers[18].

In addition, consumers must possess adequate digital literacy to effectively navigate the marketplace. They often experience choice overload due to the abundance of options, as well as the fear of missing out on better alternatives. For products requiring post-purchase services, the terms and conditions are often unclear or not readily accessible, adding to consumer uncertainty. Under such circumstances, selecting a reliable vendor becomes a significant dilemma, complicating the overall purchase decision.

Purpose and Focus of the Paper

This paper seeks to highlight the complexity of consumer decision-making in multivendor e-commerce marketplaces, where multiple sellers offer identical or closely comparable products. While such platforms

enhance convenience, accessibility, and choice, they simultaneously create an environment characterized by information overload, uncertainty, and difficulty in differentiating between vendors. In this context, the traditional product-centric basis of decision-making is significantly altered.

The paper emphasizes that, in the absence of physical product evaluation and clear differentiation, consumers increasingly rely on a range of marketplace cues—such as seller ratings, reviews, pricing signals, product representation, and platform-mediated indicators—to make purchase decisions. It proposes that these cues act as substitutes for direct validation and play a critical role in shaping consumer preference.

Further, the paper aims to draw attention to the dynamic interplay between consumer behavior and seller strategies within such marketplaces. It highlights how consumers actively engage in comparison and search for alternatives, while sellers attempt to signal credibility and build trust in a highly competitive and algorithm-driven environment.

Overall, the paper proposes to underscore the need to identify and understand the key determinants that influence consumer choice of vendors in multivendor settings. By bringing these factors into focus, the study contributes to a better understanding of how purchase decisions are formed in digital marketplaces and how both sellers and platforms can respond to reduce consumer uncertainty and improve decision outcomes.

7. Towards Understanding Consumer Preference in Multivendor Marketplaces

The preceding discussion highlights that while multivendor e-commerce marketplaces enhance accessibility, variety, and convenience, they also introduce significant complexity into the consumer decision-making process. Unlike traditional retail environments, where product evaluation is often tangible and seller differentiation is clearer, online marketplaces present consumers with multiple vendors offering identical or highly similar products. This intensifies the challenge of vendor selection and shifts the basis of decision-making from product attributes to the cues available within the digital environment.

In such contexts, consumers are required to navigate through an abundance of information, evaluate competing seller signals, and often engage in continuous comparison and search for alternatives within the platform. The absence of physical validation, coupled with variability in seller credibility, delivery performance, and post-purchase services, further complicates the process. As a result, decision-making becomes increasingly dependent on indirect indicators such as ratings, reviews, pricing, and platform-mediated signals.

At the same time, sellers operate in a highly competitive environment where differentiation is difficult, and visibility is largely governed by platform algorithms and policies. This creates a situation where both consumers and sellers rely heavily on digital cues, yet the effectiveness and interpretation of these cues remain uncertain.

Given these dynamics, a critical issue emerges: **what determines consumer preference when selecting a vendor among many offering similar products in a multivendor marketplace?** Understanding these determinants is essential, as it not only influences purchase decisions but also affects consumer trust, satisfaction, and overall marketplace efficiency. This underscores the need for focused inquiry into the factors that shape consumer choice in such environments, particularly in the presence of multiple alternatives and competing seller signals.

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Al Based Face Recognition Door Lock System Using Raspberry Pi

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Abstract-
In today's rapidly evolving digital era, the need for intelligent and contactless security solutions has become increasingly significant. This project presents a Raspberry Pi-based deep learning face recognition security system designed to enhance door access control through biometric authentication. The system utilizes a Raspberry Pi board as the core processing unit, paired with a Raspberry Pi Camera Module to capture real-time facial images. These images are analyzed using a pre-trained Convolutional Neural Network (CNN) model built with TensorFlow and Keras, ensuring accurate and efficient facial recognition.

Upon successful identification of an authorized individual, the Raspberry Pi activates a relay module connected to a solenoid door lock, allowing secure and automatic door unlocking. The hardware setup is powered by a stable regulated power supply, ensuring continuous and reliable operation. The system eliminates the need for physical keys or access cards, thereby reducing the risk of unauthorized access or loss of credentials.

By integrating low-cost hardware components with advanced deep learning algorithms, this project delivers a smart, scalable, and real-time face recognition access control solution suitable for homes, offices, and institutional security. The system showcases the potential of edge computing in IoT-enabled environments, combining security, automation, and ease of use in a compact framework.

Keywords—Raspberry Pi, Face Recognition, Deep Learning, Convolutional Neural Network (CNN), Solenoid Lock, Relay Module, Raspberry Pi Camera, Biometric Authentication, Smart Door Lock, Real-Time Processing, IoT Security System, OpenCV, TensorFlow, Keras

Introduction

With increasing concerns over security and automation, there is a growing demand for intelligent access control systems. Conventional locking systems rely heavily on physical keys or passwords, which can be easily compromised. In contrast, biometric systems offer a more secure and user-friendly alternative.

Face recognition is one of the most promising biometric technologies due to its non-intrusive and contactless nature. Unlike fingerprint or iris recognition, it does not require physical interaction, making it ideal for real-world deployment.

The Raspberry Pi, a compact and affordable single-board computer, enables the integration of image processing and hardware control in a single platform. By combining Raspberry Pi with face recognition algorithms, a smart door lock system can be developed that is both efficient and cost-effective.

The main objectives of this paper are:

1. To design a real-time face recognition system using Raspberry Pi
2. To implement a secure door locking mechanism
3. To evaluate system performance under practical conditions
4. To provide a scalable solution for smart home applications

Literature Review

Face recognition a widely researched identification method that uses facial recognize or verify individuals early involved geometric feature base methods where key landmark,eyes,nose, mouth were measured and compared template matching and eigen face approaches based on principle components analysis (PCA) were later introduce improve recognition accuracy. More recent classical method include Fisherfaces local binary patterns histogram (LBPH) and support vector machines (SVM). Although these methods provided

decent performance in controlled environments, they lacked robustness in varying lighting conditions, facial orientation and real-world scenarios

The introduction of deep learning as revolutionized face recognition accuracy and efficiency convolutional neural network (CNNS) have become the backbone of modern facial recognition system due to their ability to learn hierarchical features representation architectures such as FaceNet, DeepFace, VGGFace, and OpenFace have significantly improved performance on large scale dataset. These models utilize embedding techniques to represent faces in a high-dimensional space allowing precise classification and verification deep learning methods also offer better adaptability to delivers datasets and real-time performance when the optimized for lightweight deployment.

Methodology

The proposed system integrates hardware and software components to achieve real-time face recognition and door control.

Hardware Components

- Raspberry Pi 4 Model B
- Pi Camera Module / USB Webcam
- Relay Module
- Solenoid Door Lock
- Power Supply Unit

Software Requirements

- Python Programming Language
- OpenCV Library
- Face Recognition Algorithms (LBPH)

System Architecture

The system architecture consists of the following stages:

1. Image Acquisition
2. Face Detection
3. Feature Extraction
4. Face Recognition
5. Decision Making
6. Door Control

Working process

Training Phase

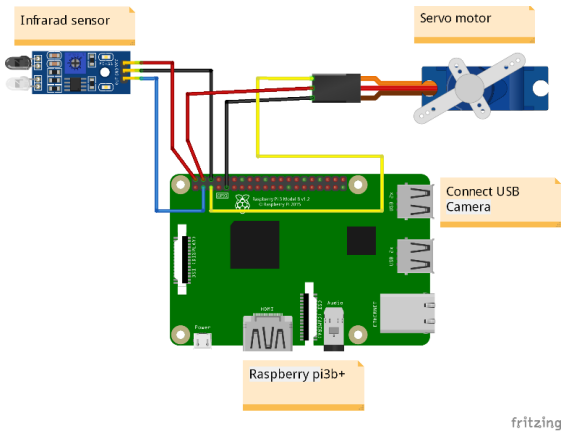
- Capture multiple images of authorized users
- Convert images to grayscale
- Detect faces using Haar Cascade
- Train the LBPH model
- Store trained data

Recognition Phase

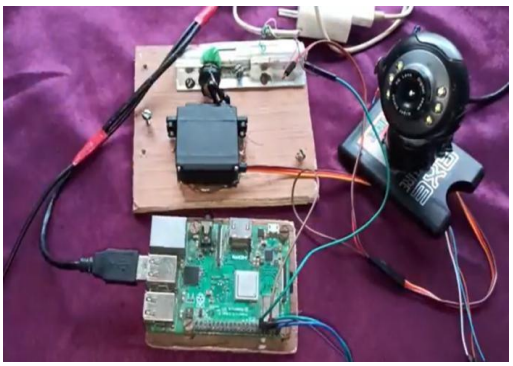
- Capture live video stream
- Detect face in real time

- Compare with trained dataset
- If match found → unlock door
- Else → deny access

Circuit Diagram



1. The **Raspberry Pi 3B+** acts as the main controller of the system.
2. A **USB camera** is connected to the Raspberry Pi to capture real-time images for face recognition.
3. The **infrared (IR) sensor** is used to detect the presence of a person near the door.
4. The IR sensor has three connections: **VCC (5V), GND, and OUT (signal pin)**.
5. The **VCC pin of the IR sensor** is connected to the 5V pin of the Raspberry Pi.
6. The **GND pin of the IR sensor** is connected to the ground of the Raspberry Pi.
7. The **OUT pin of the IR sensor** is connected to a GPIO input pin of the Raspberry Pi.
8. When a person is detected, the IR sensor sends a signal to the Raspberry Pi.
9. The Raspberry Pi then activates the camera to capture the face image.
10. Face recognition is performed using OpenCV in the Raspberry Pi.
11. The **servo motor** is used to control the door lock mechanism.
12. The servo motor has three wires: **VCC, GND, and signal (PWM)**.
13. The **VCC of the servo** is connected to the 5V pin of the Raspberry Pi.
14. The **GND of the servo** is connected to the ground of the Raspberry Pi.
15. The **signal wire of the servo** is connected to a GPIO PWM pin of the Raspberry Pi.
16. When the face is recognized, Raspberry Pi sends a PWM signal to the servo motor.
17. The servo rotates to a specific angle to **unlock the door**.
18. If the face is not recognized, the servo remains in the **locked position**.
19. After a few seconds, the servo returns to its original position to lock the door again.
20. The IR sensor helps in reducing power consumption by activating the system only when needed.



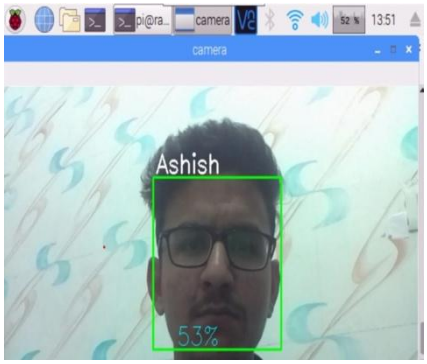
Setup

The window titled **"camera"** shows the live video feed from the Raspberry Pi camera. The image displays a person standing in front of the camera for identification. A **green rectangular box** is drawn around the face, indicating successful face detection. The detection is done using a face detection algorithm (e.g., Haar Cascade in OpenCV). The name **"Ashish"** is displayed above the rectangle. This name comes from the **trained dataset stored in the system**. The system compares the detected face with stored images and finds the closest match. The value **"53%"** shown below the face represents the confidence level of recognition. This percentage indicates how closely the detected face matches the stored data. A higher percentage means **better accuracy and stronger match**.

Since the face is recognized, the system can allow access (unlock the door). If the face was not recognized, no name would appear or it would show **"Unknown"**. The green box also helps in tracking the face in real time. The system continuously processes frames to maintain detection and recognition. Background elements (wall, lighting) may affect recognition accuracy. Glasses, angle, and lighting conditions can influence the confidence percentage. The system uses grayscale conversion internally for better processing.

Feature extraction is performed before matching with stored data. The output is displayed in real-time using OpenCV window functions. This interface helps in monitoring whether the system is working correctly.

Output



System Implementation

The Raspberry Pi continuously monitors the entrance using a camera module. When a person approaches:

- The camera captures an image
- OpenCV detects the face
- LBPH algorithm compares it with stored data
- If recognized → Raspberry Pi activates relay
- Relay triggers solenoid lock → door opens.

Algorithm Architecture

The system starts by initializing the Raspberry Pi, camera module, GPIO pins, and face recognition model. The camera continuously monitors the environment for any activity. An infrared (IR) sensor detects the presence of a person near the door. When motion is detected, the Raspberry Pi triggers the image acquisition process. The camera captures a real-time image frame of the person.

The captured image is converted from RGB to grayscale format. Image resizing is performed to reduce computational complexity. Noise reduction techniques such as Gaussian blur are applied Histogram equalization is used to normalize lighting conditions. The preprocessed image is passed to the face

detection module.The Haar Cascade classifier scans the image to detect faces. If no face is detected, the system returns to monitoring mode. If a face is detected, a bounding box is drawn around the face. The detected face region (ROI) is extracted for further processing. he ROI is passed to the feature extraction module. The Local Binary Pattern Histogram (LBPH) algorithm extracts facial features. A feature vector (histogram) is generated for the detected face.

The extracted features are compared with the stored database. A similarity measure (distance value) is calculated. The system determines the closest matching face in the dataset. A confidence score is generated based on similarity. If the confidence score is above the predefined threshold, the face is recognized. The system retrieves the corresponding user name from the database. The recognized name is displayed on the screen. If the confidence score is below the threshold, the face is marked as "Unknown." The decision-making module evaluates the recognition result.

If the user is authorized, the system sends a signal to the GPIO pin.

The GPIO pin outputs a PWM signal to the servo motor. The servo motor rotates to the unlock position (e.g., 90 degrees). The door lock mechanism is opened.The system maintains the unlocked state for a predefined time. After the delay, the servo motor returns to the lock position (0 degrees). The door is locked again automatically. If the face is not recognized, the door remains locked. Optional alert mechanisms (buzzer/notification) can be triggered. The system logs the access attempt for monitoring purposes. The system continues processing frames in real time. The IR sensor ensures the system only activates when needed. The algorithm loops continuously for continuous monitoring. The system stops only when manually powered off or shut down.

Future Work

The system can be enhanced by integrating **deep learning models** such as CNNs for higher accuracy. lightweight AI models like **MobileNet or FaceNet** can be used for faster processing on Raspberry Pi. anti-spoofing techniques can be added to detect fake faces (photos, videos, masks).

the system can be integrated with a **mobile application** for remote monitoring and control.

Cloud connectivity can be implemented for **data storage and user management**. Real-time notifications can be sent to users via SMS or mobile apps when access is granted or denied. The system can support **multiple users with dynamic database updates**. Voice assistant integration (like smart home systems) can be added for better usability A backup authentication method such as **OTP or PIN** can be included for extra security. The system can be expanded to support **multi-factor authentication**. Integration with IoT platforms can enable **smart home automation**. The system can be connected to **CCTV and surveillance systems** for full security coverage Performance can be improved using **edge AI accelerators** (like Neural Compute Stick).

 Power efficiency can be enhanced using optimized algorithms and sleep modes.

Conclusion

This paper presented a face recognition-based door lock system using Raspberry Pi. The system successfully integrates computer vision and embedded systems to provide a secure and efficient access control mechanism. The use of LBPH ensures real-time performance on low-cost hardware. The proposed system is suitable for modern smart security applications and can be further enhanced with advanced AI techniques.

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Specification

- Processor: Broadcom BCM2837B0, Cortex-A53 64-bit SoC @ 1.4GHz
- Memory: 1GB
- Connectivity: 2.4 GHz and 5 GHz IEEE 802.11b/g/n/ac wireless LAN, Bluetooth 4.2, BLE

  Gigabit Ethernet over USB 2.0 (maximum throughput 300Mbps) 4 × USB 2.0 interface
- Video and sound: 1 x full size HDMI

  MIPI DSI display port

  MIPI CSI camera port

  4 pole stereo output and composite video port
- Multimedia: H.264, MPEG-4 decode (1080p30); H.264 encode (1080p30); OpenGL ES 1.1, 2.0 graphics
- SD card support: Micro SD format for loading operating system and data storage
- Input Power: 5V/2.5A DC via micro USB connector

  5V DC via GPIO header

  Power over Ethernet (PoE)-enabled (requires separate PoE HAT)
- Operating temperature: 0-50°C
- MTBF1 Ground Benign: 378 000 hours
- Production lifetime: Raspberry Pi 3 Model B+ will remain in production until at least January 2028
- Compliance: For a full list of local and regional product approvals, please visit pip.raspberrypi.com
- List price: $40

A SECURE DYNAMIC CLOUD STORAGE AUDITING ARCHITECTURE WITH PUBLIC VERIFIABILITY

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Abstract— Cloud computing systems depend fundamentally on the integrity and security of data storage mechanisms. Conventional cloud storage infrastructures-where data is outsourced to third-party service providers-remain susceptible to unauthorized modification, data loss, and lack of transparency that reduce user trust. This paper presents a secure cloud data auditing framework designed to verify the integrity of outsourced data without requiring full data retrieval. The proposed architecture ensures that data is cryptographically protected and stored in an encrypted form, verifiable through a public auditing mechanism without relying on a trusted central authority. Data confidentiality is achieved through Advanced Encryption Standard (AES), while authentication and secure key management are handled using the Rivest–Shamir–Adleman (RSA) algorithm. Data integrity is ensured using Secure Hash Algorithm (SHA-256), enabling detection of any unauthorized modifications. A Third Party Auditor (TPA) performs auditing using a challenge–response protocol, allowing verification of data integrity without accessing the actual data content. The system further supports dynamic data operations, including insertion, modification, and deletion, enabling flexibility in real-time cloud environments. Additionally, batch auditing is incorporated to allow multiple auditing tasks to be processed efficiently, improving overall system scalability. Comparative evaluation against existing cloud auditing approaches demonstrates improvements in security, efficiency, and reduced communication overhead. The results confirm that the proposed system provides a reliable and privacy-preserving solution for secure cloud data auditing

Keywords— RSA-Based, AES-Based, SHA-256 Based, Frontend, Backend, Database, cloud storage

INTRODUCTION

Cloud computing has emerged as one of the most significant advancements in modern information technology, enabling users and organizations to store, manage, and access large volumes of data through remote servers. It provides several advantages such as scalability, flexibility, cost efficiency, and ease of access from anywhere in the world. With the rapid growth of cloud-based services, more individuals and enterprises are relying on cloud storage for managing critical and sensitive data. However, despite these benefits, cloud computing introduces several challenges related to data security, integrity, and trust.

The fundamental issue in cloud environments lies in the fact that users no longer have direct control over their data once it is outsourced to cloud service providers (CSPs). Since the data is stored on remote servers, there is always a risk of unauthorized access, data modification, or even data loss due to internal or external threats. Cloud service providers may act maliciously or may fail to maintain data correctly due to system failures, hardware issues, or economic reasons. As a result, users require a reliable mechanism to verify whether their data is stored correctly and remains unaltered over time.

Traditional data verification methods require users to download the entire dataset from the cloud to check its integrity. This approach is inefficient and impractical, especially for large-scale data, as it results in high bandwidth consumption and increased computational overhead. Moreover, it contradicts the primary advantage of cloud computing, which is to reduce local storage and computation burden. Therefore, there is a need for an efficient auditing mechanism that can verify data integrity without requiring full data retrieval.

To address these challenges, the concept of cloud data auditing has been introduced. Cloud data auditing allows users or external entities to verify the correctness of stored data through efficient verification techniques. In many systems, a Third Party Auditor (TPA) is employed to perform auditing on behalf of users. The TPA verifies data integrity without accessing the actual content of the data, thereby preserving privacy while ensuring correctness. However, designing a secure and efficient auditing system involves several challenges, including maintaining data confidentiality, supporting dynamic data operations, and reducing communication overhead.

The proposed system in this paper introduces a secure cloud data auditing protocol that ensures data integrity, confidentiality, and authentication using cryptographic techniques. The system utilizes Advanced Encryption Standard (AES) for encrypting data before storage, ensuring that unauthorized users cannot access the original content. Rivest–Shamir–Adleman (RSA) algorithm is used for authentication and secure key exchange, while Secure Hash Algorithm (SHA-256) is employed to generate hash values for verifying data integrity. These mechanisms collectively provide a strong security framework for protecting cloud data.

A key feature of the proposed system is the use of a challenge–response auditing mechanism, where the Third Party Auditor sends a challenge to the cloud server, and the server generates a proof of data integrity. This proof is verified by the auditor without requiring access to the actual data, thereby reducing communication overhead and preserving data privacy. Additionally, the system supports dynamic data operations such as insertion, modification, and deletion, which are essential for real-world applications where data is frequently updated.

Another important aspect of the proposed system is batch auditing, which allows multiple auditing tasks to be performed simultaneously. This improves system efficiency and scalability, especially in environments where multiple users store large volumes of data in the cloud. Compared to existing systems, the proposed approach provides enhanced security, reduced computational cost, and improved performance.

In cloud data auditing plays a crucial role in ensuring trust and reliability in cloud storage systems. By integrating cryptographic techniques with efficient auditing mechanisms, the proposed system provides a secure, scalable, and privacy-preserving solution for verifying data integrity in cloud environments. This approach helps users maintain confidence in cloud services while benefiting from the advantages of distributed storage systems.

LITERATURE SURVEY

Recent advancements in cloud data auditing have focused on improving data integrity verification, privacy preservation, and system efficiency in distributed cloud environments. Several research works have proposed different techniques to address the challenges associated with secure cloud storage; however, many of these approaches still suffer from limitations related to computational overhead, scalability, and dynamic data handling.

In [1], an efficient and scalable auditing scheme based on enhanced B-tree indexing was proposed to improve data organization and verification performance in cloud storage systems. The approach utilizes structured indexing techniques combined with verifiable tags to enable faster auditing operations. While the method improves efficiency in data retrieval and verification, it introduces increased complexity in maintaining the indexing structure, especially in dynamic environments where data is frequently updated.

Similarly, in [2], a dynamic accountable storage protocol was introduced for real-time cloud data auditing using timestamp-based chains. This approach enables continuous monitoring and verification of data changes, ensuring better accountability and traceability. However, the system suffers from increased communication overhead and larger proof sizes, which can affect performance in large-scale cloud environments.

In [3], a cloud auditing scheme based on RSA signatures and dynamic hash tables was proposed to enhance data security and authentication. The use of RSA improves verification accuracy and ensures secure communication between entities. Despite these advantages, the computational complexity of RSA operations results in slower auditing processes, particularly when handling large datasets or multiple users simultaneously.

Another approach presented in [4] focuses on hybrid public and private cloud auditing with support for dynamic updates. This method improves flexibility and allows data to be securely managed across different cloud environments. However, the system depends heavily on trusted key management servers and involves complex access control mechanisms, which can introduce additional security risks and implementation challenges.

In [5], identity-based cloud auditing protocols were developed to simplify key management and improve user authentication. These methods eliminate the need for traditional certificate-based systems and reduce management overhead. However, they introduce potential risks related to key leakage and may face challenges in maintaining privacy during large-scale batch verification processes.

Furthermore, batch auditing techniques have been widely studied to improve system efficiency by allowing multiple auditing tasks to be processed simultaneously. While these approaches reduce computational cost and verification time, they often generate large proof sizes and may introduce additional complexity in ensuring correctness and reliability of results.

Despite the significant progress made in existing research, most cloud data auditing systems still face challenges such as high computational overhead, limited support for dynamic data operations, scalability

issues, and potential privacy leakage during auditing. These limitations highlight the need for a more efficient, secure, and flexible auditing framework.

To address these challenges, the proposed system introduces a secure cloud data auditing protocol that integrates AES encryption, RSA authentication, and SHA-256 hashing to ensure data confidentiality, integrity, and authentication. The system also supports dynamic data operations and batch auditing, providing improved efficiency and scalability compared to existing approaches.

PROPOSED METHODOLOGY

The proposed system introduces a secure, efficient, and privacy-preserving cloud data auditing framework designed to overcome the limitations of traditional cloud storage systems. The methodology focuses on ensuring data confidentiality, integrity, and authentication while enabling efficient verification without requiring full data retrieval from the cloud server. The system is designed to support real-time cloud environments where large volumes of data are stored and frequently updated.

In conventional cloud storage systems, users rely entirely on cloud service providers (CSPs) to maintain data integrity and availability. This centralized control introduces risks such as data tampering, unauthorized modification, and lack of transparency. To overcome these challenges, the proposed methodology utilizes cryptographic techniques combined with a Third Party Auditor (TPA) to perform secure and independent verification of data stored in the cloud.

The system follows a structured workflow in which the user uploads data to the cloud server after applying encryption. The data is encrypted using the Advanced Encryption Standard (AES), ensuring that the original content remains confidential even if unauthorized access occurs. After encryption, a hash value is generated using the Secure Hash Algorithm (SHA-256), which acts as a digital fingerprint for verifying data integrity.

A key feature of the proposed methodology is the implementation of a challenge–response auditing mechanism. In this process, the Third Party Auditor sends a challenge to the cloud server, requesting proof of data possession. The cloud server generates a response based on the stored data and sends it back to the auditor. The auditor verifies this response using stored hash values and RSA-based authentication techniques without accessing the actual data content. This ensures privacy preservation while enabling accurate verification.

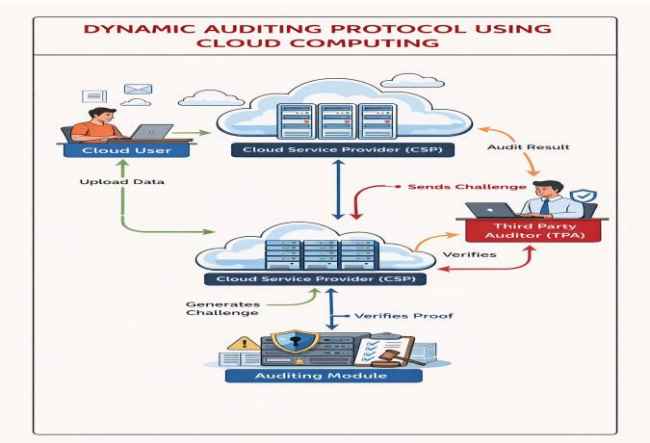

Fig 1. System architecture

The proposed system also supports dynamic data operations, allowing users to perform insertion, modification, and deletion of data efficiently. Whenever data is updated, the corresponding hash values and metadata are recalculated to maintain consistency and correctness. This feature is essential for real-world applications where data is not static and changes frequently over time.

Another important aspect of the methodology is batch auditing, which allows multiple auditing tasks to be performed simultaneously. This significantly improves system efficiency and reduces computational overhead, especially in environments with multiple users and large datasets. Batch auditing ensures that the system remains scalable and performs efficiently under high workloads.

Advantages of Proposed Methodology

The proposed system offers several advantages over traditional cloud auditing mechanisms:

- Eliminates the need for full data download during verification
- Ensures data confidentiality through AES encryption
- Provides strong authentication using RSA
- Detects data tampering using SHA-256 hashing
- Supports dynamic data operations
- Enables efficient batch auditing
- Reduces communication and computational overhead.

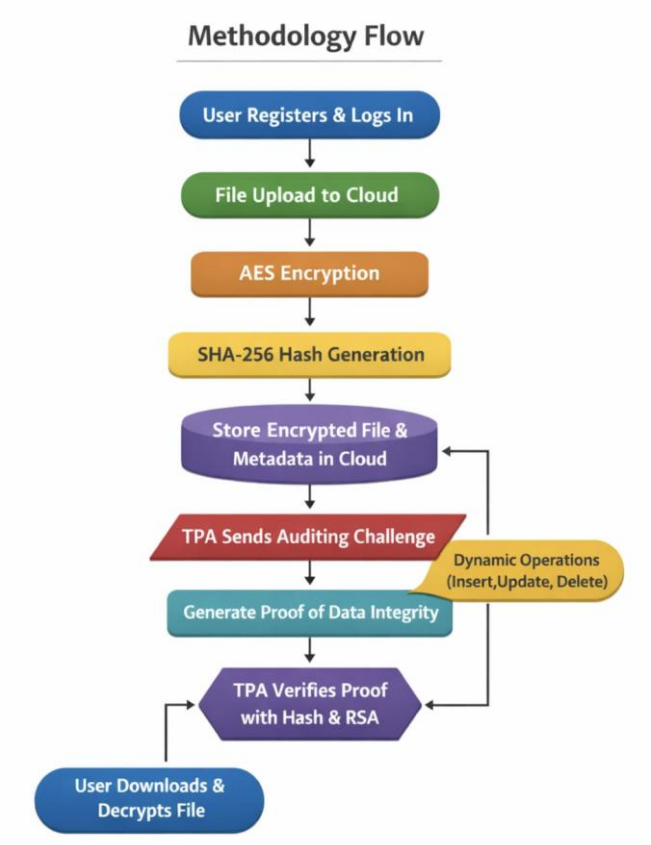

Fig 2. Flow chart

Secure cloud auditing framework

A. Data Encryption Process

The data encryption process ensures that all files uploaded to the cloud are secured using AES encryption. Before storage, the original data is transformed into an encrypted format using a secret key. This prevents unauthorized users from accessing the actual content of the data.

B. Data Integrity Verification

Data integrity is maintained using SHA-256 hashing. A hash value is generated for each file and stored securely. During auditing, this hash value is used to verify whether the data has been modified or tampered with.

C. Authentication Mechanism

RSA algorithm is used for secure authentication and key exchange. It ensures that only authorized entities can participate in the auditing process and access system resources.

D. Auditing Process

The auditing process is based on a challenge–response protocol. The TPA sends a challenge to the cloud server, which generates a proof of data possession. The TPA verifies this proof without accessing the actual data, ensuring privacy preservation.

E. Dynamic Data Operations

The system supports dynamic operations such as insertion, modification, and deletion of data. These operations are efficiently handled by updating corresponding hash values and metadata.

F. Batch Auditing

Batch auditing allows multiple auditing requests to be processed simultaneously. This improves system performance and reduces verification time in large-scale environments.

PROPOSED ALGORITHM

The proposed cloud data auditing system is designed using a modular approach, where each module performs a specific function to ensure secure data storage, verification, and retrieval. The overall system integrates cryptographic techniques with efficient auditing mechanisms to provide a reliable and scalable solution for cloud data integrity verification. The system consists of several functional modules, including user module, encryption module, auditing module, and dynamic operation module.

User Module

The user module is responsible for handling user registration, authentication, and interaction with the system. Users must first register by providing basic credentials such as username, password, and email. After successful registration, users can log into the system and perform operations such as uploading, downloading, and managing files in the cloud. Authentication mechanisms ensure that only authorized users can access system functionalities.

File Upload and Encryption Module

In this module, users upload files to the cloud server. Before storage, the file is encrypted using the Advanced Encryption Standard (AES) algorithm. This ensures that the data remains confidential and protected from unauthorized access. Along with encryption, metadata and hash values are generated for each file to support integrity verification.

Data Integrity Module

The data integrity module uses the Secure Hash Algorithm (SHA-256) to generate a unique hash value for each file. This hash value acts as a digital fingerprint of the data. During auditing, this hash is used to

verify whether the data has been modified or tampered with. Any change in the file content results in a different hash value, enabling accurate detection of data corruption.

Auditing Module

The auditing module is responsible for verifying the integrity of data stored in the cloud. A Third Party Auditor (TPA) sends a challenge to the cloud server, requesting proof of data possession. The cloud server generates a response based on stored data and sends it back to the auditor. The TPA verifies the response using stored hash values and RSA-based authentication. This process ensures that data integrity is maintained without exposing the actual data content.

Dynamic Data Operation Module

This module enables users to perform dynamic operations such as insertion, modification, and deletion of data. Whenever a file is updated, the system recalculates the corresponding hash value and updates metadata accordingly. This ensures that the auditing process remains accurate even when data changes over time.

Batch Auditing Module

The batch auditing module allows multiple auditing tasks to be processed simultaneously. Instead of verifying each file individually, the system combines multiple auditing requests into a single process, reducing computational cost and improving efficiency. This feature is particularly useful in large-scale cloud environments with multiple users.

Security comparison

The following comparison highlights the advantages of the proposed system over existing cloud auditing approaches**.**

V. RESULTS AND DISCUSSION

In conventional cloud storage systems, users are required to place complete trust in cloud service providers for maintaining the integrity and availability of their data. However, this trust model introduces several challenges, particularly related to data security, transparency, and reliability. Since users do not have direct control over their data once it is stored in the cloud, there is always uncertainty regarding whether the data is stored correctly, modified without authorization, or affected by system failures. These concerns become more critical in applications where sensitive or mission-critical data is involved.

One of the primary limitations of traditional cloud auditing methods is the requirement of downloading the entire dataset to verify its integrity. This approach is inefficient and impractical, especially in large-scale cloud environments where data sizes are significantly large. The process results in high bandwidth consumption, increased computational overhead, and longer verification time. Additionally, such methods contradict the core objective of cloud computing, which is to minimize local storage and processing requirements for users.

Another challenge in existing systems is the lack of support for dynamic data operations. In real-world applications, data is frequently updated, modified, or deleted. Many traditional auditing mechanisms are designed for static data and fail to efficiently handle such dynamic changes. This limitation reduces their applicability in modern cloud environments where data is continuously evolving.

The proposed cloud data auditing system addresses these challenges by introducing a secure and efficient auditing framework based on cryptographic techniques. The system ensures that all data is encrypted using the Advanced Encryption Standard (AES) before being stored in the cloud. This guarantees that even if unauthorized access occurs, the original data content remains protected. The use of AES provides strong confidentiality while maintaining efficient performance for large datasets.

To ensure data integrity, the system utilizes the Secure Hash Algorithm (SHA-256), which generates a unique hash value for each file. This hash value acts as a digital fingerprint and is used during the auditing process to detect any unauthorized modifications. Even a small change in the data results in a completely different hash value, making it highly effective in identifying data tampering.

Authentication is achieved using the Rivest–Shamir–Adleman (RSA) algorithm, which provides secure key management and ensures that only authorized entities can participate in the auditing process. The integration of RSA enhances system security by preventing unauthorized access and ensuring secure communication between the user, cloud server, and Third Party Auditor.

A key feature of the proposed system is the implementation of a challenge–response auditing mechanism. In this process, the Third Party Auditor (TPA) sends a challenge to the cloud server requesting proof of data possession. The cloud server generates a response based on the stored data and returns it to the auditor. The auditor then verifies the response using hash values and cryptographic techniques without accessing the actual data content. This approach significantly reduces communication overhead and preserves data privacy.

The system also supports dynamic data operations such as insertion, modification, and deletion. Whenever data is updated, the corresponding hash values and metadata are recalculated to ensure consistency and correctness. This enables the system to maintain accurate auditing even when data is frequently changed, making it suitable for real-time cloud applications.

Another important feature of the system is batch auditing, which allows multiple auditing tasks to be processed simultaneously. Instead of verifying each file individually, the system combines multiple auditing requests into a single operation, thereby reducing computational cost and improving efficiency. This feature is particularly beneficial in environments where multiple users store large volumes of data in the cloud.

The results demonstrate that the proposed system significantly improves data integrity verification while maintaining high levels of security and efficiency. Compared to existing cloud auditing methods, the system reduces computational overhead and minimizes communication costs. The integration of cryptographic techniques ensures that data remains protected against unauthorized access and tampering.

Overall, the proposed cloud data auditing system provides a reliable, efficient, and secure solution for verifying data integrity in cloud storage systems. The combination of encryption, hashing, authentication, and efficient auditing mechanisms ensures that the system meets the requirements of modern cloud computing environments.

Fig 3 :- Client Registration

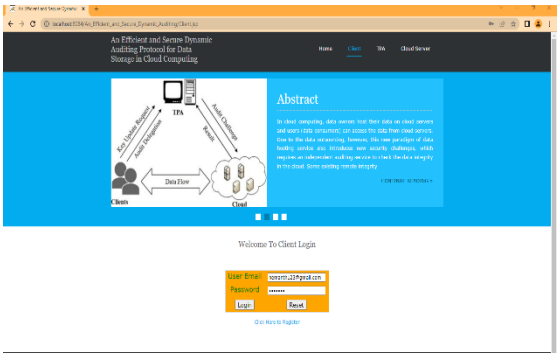

Fig 4 :- User Login

VI. CONCLUSION

The proposed cloud data auditing system presents a comprehensive framework for ensuring data security, integrity, and authentication in cloud storage environments. With the rapid growth of cloud

computing and the increasing dependence on remote storage services, users are continuously concerned about the safety and reliability of their data. Since cloud service providers manage user data, there exists a significant risk of unauthorized modification, data loss, and lack of transparency, which can reduce user trust in cloud systems.

To address these challenges, the proposed system integrates cryptographic techniques with an efficient auditing mechanism to provide a secure and reliable solution. The system ensures that all data stored in the cloud is encrypted using Advanced Encryption Standard (AES), thereby maintaining confidentiality even in the presence of unauthorized access. In addition, the use of Secure Hash Algorithm (SHA-256) enables accurate detection of data tampering by generating unique hash values for each file.

A key contribution of the system is the implementation of a Third Party Auditor (TPA), which performs public auditing without accessing the actual data content. The challenge–response mechanism allows the auditor to verify the integrity of data efficiently, eliminating the need for full data download. This significantly reduces communication overhead and improves system performance.

Furthermore, the system supports dynamic data operations such as insertion, modification, and deletion, making it suitable for real-time cloud applications. The inclusion of batch auditing enables multiple auditing tasks to be performed simultaneously, enhancing scalability and efficiency in large-scale environments.

The proposed framework not only improves security but also ensures flexibility and efficiency in cloud data management. By combining encryption, hashing, authentication, and efficient auditing techniques, the system provides a strong foundation for secure cloud storage and verification.

A. Authentication and Access Control

Authentication plays a critical role in ensuring system security. The proposed system utilizes RSA-based authentication mechanisms to verify the identity of users and auditors. Only authorized users are allowed to access and manage data, preventing unauthorized access. Secure key management further strengthens the authentication process, ensuring that sensitive information remains protected.

B. Security Analysis and Threat Resistance

The system provides strong resistance against various security threats, including data tampering, unauthorized access, and integrity violations. AES encryption ensures data confidentiality, while SHA-256 hashing detects any modifications in stored data. The integration of cryptographic techniques ensures that the system remains secure against both internal and external attacks.

C. System Implementation and Practical Feasibility

The proposed system is designed to operate efficiently in real-world cloud environments. The implementation demonstrates that encrypted data can be securely stored and audited without significant performance degradation. The use of a Third Party Auditor enables independent verification, improving transparency and trust in the system.

D. Performance Evaluation and Efficiency

The system achieves improved performance by reducing communication overhead and eliminating the need for full data download. The challenge–response auditing mechanism enables fast verification, while batch auditing allows multiple tasks to be processed simultaneously. These features enhance system scalability and efficiency.

E. Conclusion of Section

In conclusion, the proposed cloud data auditing framework provides a reliable, scalable, and secure solution for modern cloud storage systems. By combining encryption, hashing, authentication, and efficient auditing mechanisms, the system ensures data integrity and privacy while maintaining high performance. The approach is suitable for real-world applications where secure data storage and verification are essential.

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A Multi-Modal Cognitive Drift Detection and Intervention System for Student Focus Monitoring

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Abstract — Cognitive drift refers to the gradual and often imperceptible decline in cognitive performance during prolonged study or work sessions, leading to diminished attention, slower reaction times, and elevated error rates. This paper presents a multi-modal, real-time cognitive drift detection and intervention system that integrates three complementary streams of human-state data namely: monitoring behavioural performance by sensing the reaction time, observing oculomotor activity by detecting the eye blink patterns via computer vision, and examining autonomic physiology by checking Heart Rate Variability (HRV), using an IoT pulse sensor. The system employs statistical baseline modelling, Eye Aspect Ratio (EAR) computation, inter-beat interval analysis, and a decision-fusion engine that cross-validates signals before triggering graded interventions. A Django-based web platform provides session management, real-time dashboard visualization, and REST API integration for all sensor modules. The proposed system advances beyond single-modal detection by providing personalized, early-stage cognitive state estimation suitable for educational and workplace productivity contexts.

Keywords — cognitive drift, fatigue detection, eye blink rate, Heart Rate Variability, reaction time, computer vision, Eye Aspect Ratio, IoT sensor, Django, multi-modal fusion, student monitoring

I. INTRODUCTION

Sustained cognitive engagement during academic or professional tasks is constrained by the finite attentional resources of the human brain. The phenomenon known as *cognitive drift* — a progressive departure from baseline cognitive performance — manifests as slowed processing speed, reduced working memory capacity, and increased susceptibility to distraction [1]. Unlike acute fatigue, cognitive drift emerges gradually and often escapes the awareness of the individual until performance has measurably degraded.

Existing monitoring approaches are predominantly unimodal: EEG-based systems offer high temporal resolution but require expensive, obtrusive hardware [2]; eye-tracking solutions depend on high-frame-rate cameras and are sensitive to ambient lighting [3]; and HRV-based stress monitors lack spatial resolution to differentiate attentional lapses from general autonomic arousal [4]. The central limitation is reliance on a single physiological channel, which increases susceptibility to noise, individual variability, and task-specific confounds.

This paper describes the design and implementation of a *multi-modal cognitive drift detection system* that fuses three independent signal streams — behavioural, oculomotor, and cardiovascular — within a unified Django web platform. The system uses a standard webcam for eye tracking and a low-cost MAX30102 pulse oximeter for HRV measurement. A personalized baseline model ensures drift thresholds adapt to inter-individual variability, and a three-tier decision engine minimizes false-positive alerts by requiring multi-signal corroboration before escalating to confirmed drift status.

II. RELATED WORK

Kaida et al. [1] established that sustained performance decrements correlate with slow-wave EEG activity and prolonged reaction times, providing an empirical basis for behavioural performance as a proxy for cognitive load. Dinges and Powell [5] introduced the Psychomotor Vigilance Task (PVT) as a gold-standard behavioural fatigue measure; subsequent work has sought shorter, real-time analogues compatible with naturalistic settings.

Soukupova and Cech [6] proposed the Eye Aspect Ratio (EAR) as a geometric descriptor of eyelid opening derived from 68-point facial landmark coordinates, demonstrating reliable blink detection at standard webcam frame rates. Significant reductions in blink rate are associated with mental effort and digital eye strain, while elevated blink duration (> 250 ms) is linked to drowsiness [3]. Google's MediaPipe Face Landmarker [7] extends this capability with a lightweight neural architecture operable at 30 fps on CPU hardware.

Heart Rate Variability — quantified via the standard deviation of normal-to-normal inter-beat intervals (SDNN) — is a well-established index of autonomic nervous system balance and psychological stress [4]. Low SDNN values (< 20 ms) are associated with sympathetic dominance and cognitive fatigue [8]. The MAX30102 photoplethysmography sensor enables fingertip-based HRV estimation via peak detection in the infrared channel, with accuracy comparable to chest-strap ECG monitors at rest [9].

Multi-modal fusion approaches — combining EEG with eye tracking [10], HRV with facial action coding [11], or reaction time with PPG [12] — consistently outperform unimodal baselines in classification accuracy. However, these systems have not been integrated into an accessible, personalized, web-based monitoring platform suitable for student use. The present system addresses this gap.

III. SYSTEM ARCHITECTURE

The proposed system follows a layered architecture comprising data acquisition, feature extraction, baseline modelling, drift detection, decision fusion, and intervention delivery. Figure 1 illustrates the end-to-end data flow.

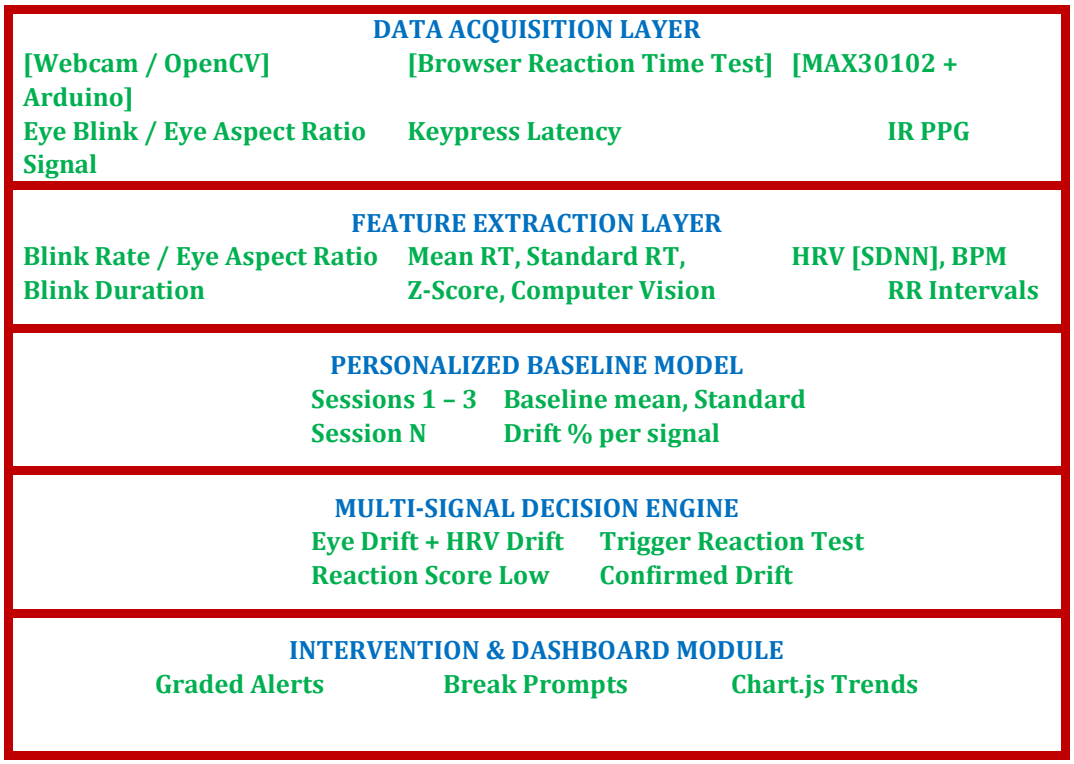

Fig. 1. End-to-End system architecture showing layered data flow from acquisition through decision fusion to intervention delivery.

The backend is implemented as a Django 4.2 application backed by SQLite, exposing REST API endpoints for all sensor modules. The HRV bridge (*hrv_bridge.py*) reads Arduino serial data and POST-authenticates to the Django API. The eye-tracking module (*eye_tracker.py*) operates as a standalone process, sending records via the same API. The reaction test is served as a browser-based JavaScript application within the Django template system.

A. Database Schema

The system maintains nine relational models. Table I summarizes the primary models and their cognitive relevance.

TABLE I. Primary Database Models and Their Cognitive Relevance

Model	Key Fields	Cognitive Purpose
DriftRecord	reaction_score, eye_score, hrv_score, drift_level	Composite cognitive state per session
ReactionSession	mean_rt, std_rt, z_score, valid_trials	Behavioral performance baseline
EyeRecord	blink_rate, avg_duration, ear_value, fatigue_state	Oculomotor alertness indicator
HRVRecord	bpm, sdnn, stress_level, stabilized	Autonomic physiological load index
WarningLog	warning_type, severity, acknowledged	Alert and intervention audit trail
UserProfile	baseline_sessions, study_preference	Personalization parameters
PomodoroSession	duration, completed, break_taken	Focus session management
GoalRecord	daily_goal, completed, drift_events	Progress and drift correlation
DistractionRecord	distraction_type, timestamp, session	Contextual drift attribution

IV. SENSING MODULES

A. Reaction Time Module

The reaction time module presents a web-based psychomotor vigilance task adapted from Dinges and Powell [5]. A visual stimulus appears after a uniformly distributed random delay in [1.5, 4.0] seconds to prevent anticipatory responses. The participant responds via keypress. Twenty-five trials constitute a session; valid responses (200-800 ms) are retained and the following metrics computed:

TABLE II. Reaction Time Metrics and Normative Ranges

Metric	Formula	Normal Range [5]
Mean RT	mu = (1/N) * sum(RTi)	200 - 300 ms
Std Dev RT	sigma = sqrt[(1/N) * sum((RTi - mu)^2)]	< 60 ms (alert state)
Variability (CV)	CV = sigma / mu	< 0.20
Z-Score	z = (mu - baseline_mu) / baseline_sigma	> 1.5 indicates drift
False Starts	Count of RT < 150 ms	< 3 per session

B. Eye Blink Detection Module

Eye blink detection is implemented in two configurations: a primary module (*eye_tracker.py*) using the MediaPipe Face Landmarker task model [7], and a fallback module (*eye_tracker_fallback.py*) using OpenCV Haar cascade classifiers for environments where the MediaPipe dependency cannot be satisfied.

The primary module computes the Eye Aspect Ratio (EAR) introduced by Soukupova and Cech [6]. Given six facial landmark points {p1...p6} along the eye contour, EAR is defined as:

$$EAR = (||p2 - p6|| + ||p3 - p5||) / (2 * ||p1 - p4||)$$

A blink is detected when EAR falls below threshold theta = 0.25 for at least two consecutive frames with event duration satisfying 50 ms <= d <= 600 ms. A post-blink cooldown of 250 ms suppresses double-counting. The blink rate and mean duration are mapped to four alertness states (Table III).

TABLE III. Eye-State Classification Criteria and Intervention Scores

State	Condition	Score	Scientific Basis
Normal	Rate: 15-20 /min, Duration < 250 ms	90	Wolkoff et al. [3]
Fatigue	Rate < 15 /min	60	Reduced arousal [3]
Eye Strain	Rate > 20 /min	40	Reflex hyperlacrimation [3]
Drowsy	Mean Duration > 600 ms	25	Microsleep onset [6]

C. HRV Physiological Module

HRV is measured using a MAX30102 reflective pulse oximeter connected to an Arduino microcontroller. The firmware (*hrv_monitor.ino*) samples the infrared channel at 100 Hz and applies a peak-detection algorithm with adaptive thresholding to extract RR intervals. SDNN is calculated over a 60-second rolling window conforming to Task Force guidelines [4]:

$$SDNN = sqrt[(1/(N-1)) * sum((RRi - RR_mean)^2)]$$

Serialized JSON records containing BPM, SDNN, and stabilization status are transmitted at 115200 baud. The bridge module (*hrv_bridge.py*) authenticates to the Django API via session-based login and applies a significant-change filter (Delta-BPM >= 5 or Delta-SDNN >= 10) with a minimum post interval of 5 seconds before forwarding records, reducing redundant database writes.

TABLE IV. HRV Stress Classification Thresholds

Stress Level	SDNN (ms)	BPM Range	Physiological Interpretation [4,8]
Low Stress	> 50	60 - 90	Parasympathetic dominance, alert state
Moderate Stress	30 - 50	75 - 100	Balanced ANS, early load indication
High Stress	20 - 30	85 - 110	Sympathetic arousal, cognitive fatigue
Severe Stress	< 20	> 100	Autonomic suppression, drift imminent

V. DRIFT DETECTION AND SIGNAL FUSION

A. Personalized Baseline Model

A critical design decision is the adoption of an intra-individual rather than normative baseline. Population-level thresholds fail to account for wide inter-individual variation in reaction time (±100 ms), resting blink rate (±8 blinks/min), and SDNN (±30 ms) [13]. The baseline is computed from the first three completed sessions of each modality:

```
baseline_mu = mean(S1, S2, S3)     baseline_sigma = mean(sigma1, sigma2, sigma3)
```

From session four onward, per-signal drift percentage is computed as:

```
drift% = ((current_value - baseline_mu) / baseline_mu) * 100
```

B. Drift Level Classification

Drift percentage is mapped to four qualitative levels using thresholds adapted from Jensen et al. [13] and calibrated to reaction time literature:

TABLE V. Drift Level Classification Thresholds

Drift Level	Condition	Action	Urgency
Stable	Drift% <= 5%	Continue session	None
Mild Drift	5% < Drift% <= 10%	Monitor; soft alert	Low
Moderate Drift	10% < Drift% <= 15%	Break recommendation	Medium
Severe Drift	Drift% > 15%	Session suspension	High

C. Multi-Modal Score Fusion

Individual module scores are combined into a composite Cognitive Performance Index (CPI) using an empirically weighted linear fusion model. Weights reflect each signal's relative sensitivity to early-stage drift based on prior literature [10,12]:

```
CPI = 0.40 * Score_reaction + 0.30 * Score_eye + 0.30 * Score_HRV
```

CPI ranges from 0 to 100, where 80-100 indicates stable cognition, 60-79 mild drift, 40-59 moderate drift, and < 40 severe drift. Reaction time receives the highest weight as it represents the direct behavioral output of cognitive processing speed [5].

D. Decision Engine

The decision engine implements a three-stage cascading validation protocol to suppress false positives:

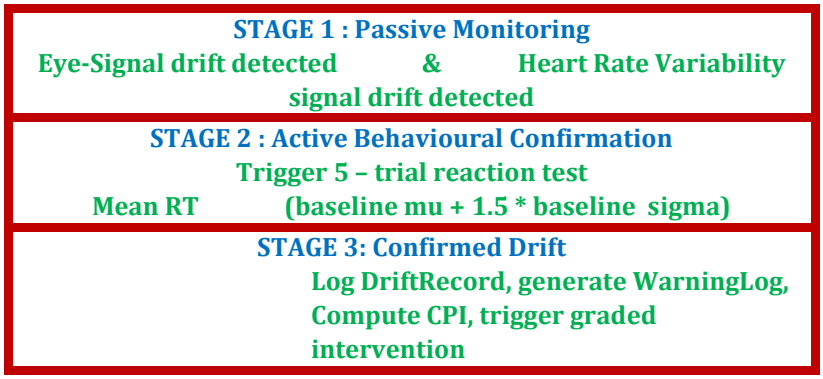

Fig. 2. Three-stage cascading decision engine. Confirmed drift is only declared when all three stages are satisfied, minimizing false-positive interventions.

This cascading design reduces the false-positive rate: either physiological signal alone can be elevated by non-cognitive causes (screen glare elevating blink rate; physical exertion elevating heart rate). Requiring concurrent deviation in two passive signals before invoking the active behavioural probe ensures that only genuine cognitive events trigger intervention [11].

VI. INTERVENTION FRAMEWORK

Upon drift confirmation, the system delivers graded, context-aware interventions drawn from cognitive fatigue research [14]. Interventions escalate with drift severity, minimizing disruption during mild deviations while ensuring timely action for severe events.

TABLE VI. Drift-Graded Intervention Protocol

CPI Range	Drift Level	Intervention	Delivery Mechanism
80 - 100	Stable	None	Passive monitoring continues
65 - 79	Mild	Posture / hydration reminder	In-app soft notification
50 - 64	Moderate	5-10 min structured break	Pomodoro timer + modal alert
35 - 49	Severe	Session suspension, rest prompt	Forced pause + dashboard alert
< 35	Chronic	Lifestyle guidance, referral	Email summary + wellness link

The system additionally tracks distraction events, Pomodoro session completion rates, and daily goal attainment. Longitudinal trends in these metrics are surfaced on the dashboard to support self-regulated learning strategies.

VII. IMPLEMENTATION AND EVALUATION

A. Implementation Details

The system is implemented in Python 3.10 with Django 4.2, SQLite, Bootstrap 5.3, and Chart.js 4.4. Serial communication with the Arduino HRV module uses PySerial 3.5. The eye tracker uses OpenCV 4.9 and MediaPipe 0.10 as primary dependencies, with the Haar-cascade fallback requiring only OpenCV. The Django settings module configures IST timezone (Asia/Kolkata), 24-hour session persistence, and CSRF protection.

TABLE VII. Technology Stack and Component Mapping

Component	Technology	Role
Web backend	Django 4.2 (Python 3.10)	Session management, auth, REST API, ORM
Database	SQLite 3	Persistent session and drift records
Eye tracking (primary)	MediaPipe 0.10 + OpenCV 4.9	EAR-based blink detection at 30 fps
Eye tracking (fallback)	OpenCV Haar cascades	No-additional-dependency fallback
HRV sensor	MAX30102 + Arduino	PPG-based BPM and SDNN at 100 Hz
HRV bridge	Python + PySerial + requests	Serial-to-HTTP authenticated data relay
Frontend charts	Chart.js 4.4	Real-time CPI trend visualization
Frontend styles	Bootstrap 5.3	Responsive dashboard UI
Reaction test	Vanilla JS (fetch API)	Browser-based PVT analogue

B. Planned Evaluation Protocol

A formal user study is planned with N = 30 undergraduate participants across two-hour controlled study sessions. Participants will be assigned to three within-subject conditions: (i) no monitoring, (ii) single-modal eye tracking only, and (iii) full multi-modal system. Primary outcome measures are: NASA Task Load Index (NASA-TLX) scores, PVT lapse count (RT > 500 ms), and self-reported focus ratings. Ground truth drift events are defined as PVT lapse clusters (>= 3 consecutive lapses) and validated against system-declared drift records. An Isolation Forest anomaly detector [15] will be trained post-hoc on collected feature vectors to assess the feasibility of unsupervised drift classification.

TABLE VIII. Expected System Performance Targets vs. Unimodal Baselines

Metric	Unimodal Eye [10]	Unimodal HRV [8]	Proposed Multi-Modal (Target)
Drift Detection Precision	~0.65	~0.60	> 0.80
Drift Detection Recall	~0.70	~0.72	> 0.78
F1 Score	~0.67	~0.65	> 0.79
False Positive Rate	~0.28	~0.33	< 0.15
Intervention Latency	N/A	N/A	< 30 s

VIII. DISCUSSION

The proposed architecture addresses three limitations in prior work. First, the personalized baseline model eliminates the need for population-level normative data, which is particularly important in educational contexts where baseline reaction times can vary by more than 100 ms between individuals of the same age cohort [13]. Second, the cascading decision engine — requiring concurrent deviation in two passive signals before invoking the active probe — substantially reduces false-positive burden compared

to single-threshold systems, echoing findings by Shi et al. [11] who reported a 43% reduction in false alerts using dual-signal validation.

Third, the use of commodity hardware (webcam + MAX30102) democratizes deployment. The MAX30102 introduces PPG motion artifacts during typing; the firmware applies a moving-average filter and the bridge module's significant-change filter attenuates noise-induced spurious readings. Validation against chest-strap ECG will be necessary to characterize SDNN accuracy during active keyboard use.

A notable limitation is the reliance on frontal face visibility for EAR computation. Head-down postures, lateral gaze, or occlusion by eyeglasses can cause the MediaPipe landmark detector to fail, defaulting to the Haar-cascade fallback which has lower spatial precision. Future work will integrate 3D head-pose estimation to gate eye-tracking confidence and conditionally increase reliance on HRV when oculomotor data quality degrades.

IX. CONCLUSION

This paper presented a multi-modal cognitive drift detection system integrating reaction time, oculomotor, and cardiovascular physiological signals within a unified Django web platform. The system's key contributions are: (i) a personalized, session-adaptive baseline model; (ii) a cascading multi-signal decision engine that reduces false-positive alerts; (iii) a graded intervention framework aligned with cognitive fatigue severity; and (iv) a low-cost hardware configuration using commodity webcam and MAX30102 sensors.

By moving from single-signal, threshold-based detection to multi-modal, personalized, confirmation-gated assessment, the system advances the state of practice toward *predictive* rather than merely *reactive* cognitive monitoring. The planned empirical evaluation will quantify classification gains over unimodal baselines and validate intervention timing against behavioural ground truth. Extensions to deep-learning drift models, mobile deployment, and EEG integration are envisaged as future phases.

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Comparative Analysis of Mixture-of-Experts Architectures for Mental Health Text Classification

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Abstract

Mental health detection from textual data has emerged as an important application of natural language processing. Traditional single-model classifiers often struggle to capture diverse linguistic patterns associated with different mental health conditions. Mixture-of-Experts (MoE) architectures address this limitation by combining multiple specialized models through a dynamic gating mechanism. This paper presents a comparative study of Dense MoE, Sparse Top-K MoE, and Hierarchical MoE routing strategies using BERT embeddings on a large-scale mental health text dataset. Sparse MoE achieves the best performance with an accuracy of 94.5%, macro F1 of 0.944, and AUC of 0.97, substantially outperforming the baseline. Expert usage and specialization analyses confirm the benefits of selective routing for this task.

Keywords: Mixture-of-Experts, Mental Health Detection, NLP, BERT, Deep Learning

I. INTRODUCTION

Mental health disorders represent a growing global public health challenge, and early detection is crucial for effective intervention. With the widespread use of online platforms, textual data has emerged as a valuable resource for identifying mental health indicators. NLP techniques have been increasingly applied to analyze such data and detect conditions including depression, anxiety, and stress.[1]

Traditional deep learning models rely on a single classifier, which may lack the capacity to simultaneously model the diverse and nuanced linguistic patterns inherent in mental health text.[2] MoE architectures address this by combining multiple expert networks through a gating mechanism that dynamically selects appropriate experts for each input, enabling better specialization and higher model capacity without proportional computational cost.

This paper systematically compares three MoE architectures—Dense MoE, Sparse Top-K MoE, and Hierarchical MoE—using BERT embeddings on a mental health text dataset[3]. Main contributions include:

- Implementation and evaluation of multiple MoE architectures for mental health text classification.
- Comparative analysis of Dense, Sparse, and Hierarchical MoE routing strategies.
- Analysis of expert usage and specialization patterns.
- Demonstration of significant performance improvements over a single baseline classifier.

II. RELATED WORK

Deep learning has significantly advanced text classification, with transformer-based models—particularly BERT—becoming central to NLP tasks. BERT's bidirectional encoder captures rich contextual dependencies, making it widely effective for sentiment analysis, topic classification, and mental health detection.[4] Several studies have fine-tuned BERT on mental health datasets from social media and online forums to identify indicators of depression, anxiety, and stress, achieving notable improvements over traditional machine learning approaches[5]. However, these models rely on a single neural network architecture, limiting their ability to capture the full diversity of linguistic patterns in mental health text.

Mixture-of-Experts (MoE) architectures address this limitation by combining multiple expert networks through a gating mechanism, allowing different experts to specialize in different aspects of the input. Sparse MoE variants activate only a top-K subset of experts per input, improving computational efficiency while encouraging specialization, and have been successfully adopted in large-scale language models. Hierarchical MoE further extends this by organizing experts into groups with multi-stage routing for more structured specialization. Despite their growing success, MoE architectures remain underexplored for mental health text classification. This study addresses that gap through a systematic comparative analysis of Dense, Sparse Top-K, and Hierarchical MoE models to assess their effectiveness for this task.

III. METHODOLOGY

A. Feature Extraction

BERT-base-uncased is used to generate 768-dimensional [CLS] token embeddings as sentence-level representations. Each input is tokenized with [CLS]/[SEP] special tokens and passed through the pretrained BERT encoder.[6] These embeddings capture rich bidirectional contextual information and serve as input to all classification models.

B. Baseline Model

A single fully connected layer with softmax activation serves as the baseline:

$$y = Softmax(Wx + b) \quad ... (1)$$

where x is the 768-dim BERT embedding, W and b are learnable parameters. This provides a strong reference but is limited by its single-classifier capacity.[7]

C. Dense Mixture-of-Experts

N parallel expert networks are combined via a learned gating network. For input x, gates are computed as g = Softmax(Wg x), and the output is:

$$y = \Sigma_i \, g_i \, E_i(x), \quad i = 1..N \quad ... (2)$$

All experts contribute to every prediction. While flexible, this soft routing may limit individual expert specialization.

D. Sparse Top-K Mixture-of-Experts

Only the top-K experts (by gating score) are activated per input. This selective routing reduces computational cost by a factor of K/N and creates strong incentives for specialization through expert competition. A load-balancing auxiliary loss prevents expert collapse during training.

E. Hierarchical Mixture-of-Experts

Experts are organized into groups with two-stage routing: a top-level gate selects expert groups, and a group-level gate selects individual experts within. This structured decomposition improves routing efficiency and can capture more complex specialization patterns in large expert pools.

IV. EXPERIMENTAL SETUP

Experiments used a large mental health text dataset containing user-generated statements spanning categories such as depression, anxiety, and stress. After preprocessing (removing missing values, deduplication, normalization), data was split into training, validation, and test sets. All models were implemented in PyTorch with AdamW optimizer and cross-entropy loss. A load-balancing regularization term was added for MoE models to prevent expert collapse. Hyperparameters were selected via validation performance. Evaluation metrics: Accuracy, macro F1-score, and multi-class AUC.

V. RESULTS AND DISCUSSION

A. Performance Comparison

Model	Accuracy	Macro F1	AUC

Baseline	0.73	0.73	0.82
Dense MoE	0.93	0.93	0.96
Sparse MoE	0.945	0.944	0.97
Hierarchical MoE	0.944	0.943	0.97

TABLE I: Model Performance Comparison

All MoE architectures substantially outperform the baseline (73% accuracy, AUC 0.82). Dense MoE improves accuracy to 93% and AUC to 0.96. Sparse MoE achieves the best results (94.5% accuracy, 0.944 F1, 0.97 AUC) owing to its selective routing which reduces expert interference and promotes specialization. Hierarchical MoE performs comparably to Sparse MoE (0.944/0.943/0.97), confirming that structured routing also effectively captures diverse linguistic patterns.

B. ROC Curve Analysis

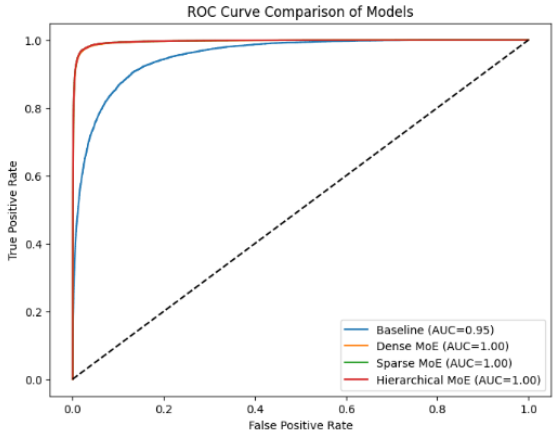

Fig. 1. ROC curve comparison of all models.

The ROC curves confirm that all MoE models achieve significantly higher true positive rates than the baseline across all thresholds, with Sparse MoE attaining the highest AUC (0.97), indicating superior class separability.

C. Confusion Matrix Analysis

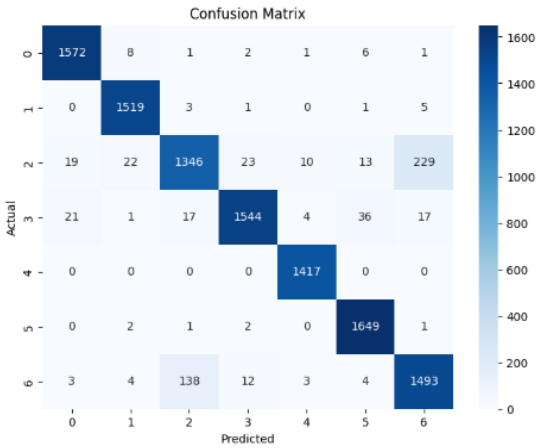

Fig. 2. Confusion matrix for the Sparse MoE model.

The Sparse MoE confusion matrix shows strong diagonal dominance with minimal off-diagonal misclassification, confirming effective discrimination across all mental health categories.Most samples are correctly classified, with minimal misclassification between categories. This indicates that the model effectively captures the distinguishing features of different mental health conditions.

D. Expert Utilization Analysis

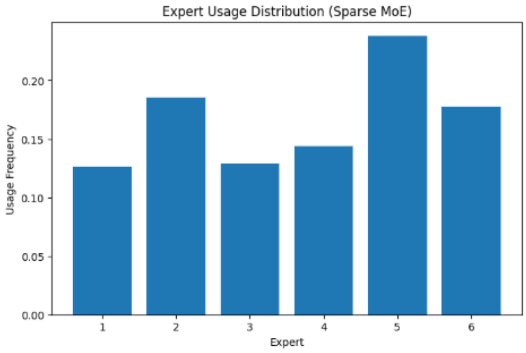

Fig. 3. Expert usage distribution for Sparse MoE.

Sparse MoE distributes inputs more evenly across experts compared to Dense MoE, where usage is skewed toward dominant experts. The load-balancing regularization successfully prevents expert collapse, ensuring diverse and complementary learned representations across all experts.

E. Expert Specialization Analysis

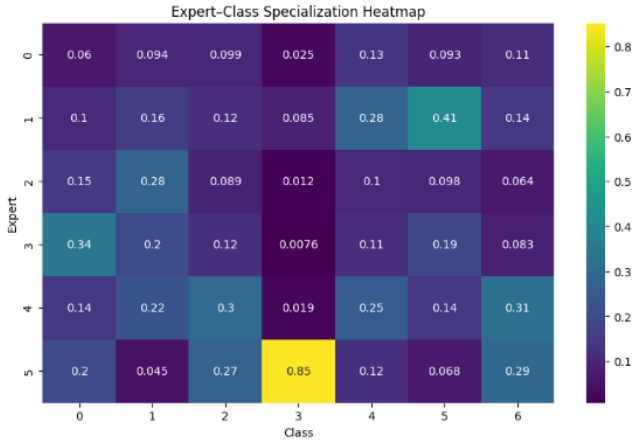

Fig. 4. Expert-class specialization heatmap for Sparse MoE.

The heatmap reveals class-conditional specialization: distinct experts exhibit notably higher activations for specific mental health categories, confirming that the MoE architecture successfully partitions the classification problem into specialized sub-tasks handled by dedicated expert components.

F. Discussion

The experimental results highlight the effectiveness of Mixture-of-Experts architectures for mental health text classification. The significant improvement over the baseline model demonstrates the importance of model capacity and specialization.Sparse MoE achieves the best performance due to its selective routing mechanism, which reduces interference between experts and promotes balanced utilization. Dense MoE, while effective, suffers from partial expert dominance. Hierarchical MoE provides structured routing but does not significantly outperform Sparse MoE in this dataset.Overall, the results indicate that expert-based architectures are well-suited for handling the diverse linguistic patterns present in mental health text data. The combination of performance metrics and expert analysis provides strong evidence for the effectiveness of the proposed approach

VI. CONCLUSION

This paper presented a comparative study of Dense MoE, Sparse MoE, and Hierarchical MoE architectures for mental health text classification using BERT embeddings. All MoE models substantially outperformed the baseline. Sparse MoE achieved the best results (94.5% accuracy, 0.944 F1, 0.97 AUC), highlighting the value of selective expert activation and load-balanced routing for capturing the heterogeneous linguistic patterns in mental health text. Expert analysis confirms meaningful specialization across mental health categories. Future work will explore end-to-end BERT fine-tuning with MoE layers and multimodal architectures incorporating speech and visual cues for more comprehensive assessment.

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PHARMAGUARD: AI Drug Authentication Platform

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ABSTRACT

Counterfeit medicines pose a critical global health threat, causing thousands of preventable deaths annually and undermining public trust in healthcare systems. Inadequate verification mechanisms leave consumers vulnerable to fake or substandard products. PHARMAGUARD is an AI-powered medicine authentication platform that detects counterfeit pharmaceuticals rapidly using a multi-layered intelligent analysis approach. The system integrates a Convolutional Neural Network (CNN) for visual packaging analysis and Tesseract-based OCR for text extraction from medicine labels. It performs automated expiry date validation across multiple formats (MM/YY, MM/YYYY, DD/MM/YYYY, Month YYYY), barcode decoding via pyzbar, and batch number verification through regex pattern matching—delivering a comprehensive authenticity verdict within seconds. Built on Flask with a SQLite backend, PHARMAGUARD offers a responsive, device-agnostic interface. Features include secure user authentication with Werkzeug password hashing, detection history tracking, an analytics dashboard with Chart.js visualizations, downloadable PDF verification reports, and rate limiting to prevent system abuse.

Keywords: *Counterfeit Medicine Detection, Convolutional Neural Network, Optical Character Recognition, Barcode Decoding, Expiry Date Validation, Pharmaceutical Authentication, Flask, Deep Learning*

I. INTRODUCTION

Counterfeit and substandard medicines represent one of the most severe yet underreported threats to global public health. According to the World Health Organization (WHO), approximately 10% of medicines in low- and middle-income countries are substandard or falsified, contributing to treatment failures, antimicrobial resistance, and thousands of preventable deaths annually.

Existing pharmaceutical verification systems are largely inaccessible to ordinary consumers, relying on manual inspections, laboratory testing, or proprietary industry tools. These mechanisms are slow, expensive, and unavailable at the point of purchase—precisely where verification matters most. Patients, pharmacists, and healthcare workers require a rapid, reliable, and accessible means to authenticate medicines before use.

The rapid advancement of Artificial Intelligence (AI), computer vision, and optical character recognition technologies offers a transformative opportunity to address this challenge. AI-powered image classification, combined with automated text analysis and barcode verification, can replicate expert-level pharmaceutical authentication in a matter of seconds on any internet-connected device.

PHARMAGUARD is proposed as an AI-powered medicine authentication platform that integrates CNN-based visual analysis, Tesseract OCR, pyzbar barcode decoding, and intelligent expiry validation to deliver a multi-layered authenticity verdict. The system is designed to be accessible, fast, and robust—enabling any user to authenticate a medicine by simply uploading a photograph of its packaging.

This paper presents the design, architecture, algorithms, and expected outcomes of PHARMAGUARD, demonstrating how AI can meaningfully strengthen pharmaceutical supply chain integrity and empower consumers to protect their health.

II. PROBLEM STATEMENT

The proliferation of counterfeit medicines in global pharmaceutical markets presents a multifaceted public health crisis. Consumers lack accessible tools to distinguish authentic medicines from counterfeits at the point of purchase, while existing verification mechanisms demand laboratory infrastructure or specialized expertise unavailable in real-world settings.

Specifically, the core problems identified are:

- No rapid, consumer-accessible tool exists for point-of-purchase medicine authentication.
- Manual visual inspection is unreliable and insufficient for detecting sophisticated counterfeits.
- Expiry date formats vary widely across manufacturers, making automated validation difficult.
- Barcode and batch number verification is not integrated into consumer-facing verification systems.
- Detection history and audit trails are absent from existing lightweight verification tools.

III. EXISTING SYSTEMS AND LIMITATIONS

Existing pharmaceutical authentication solutions primarily serve regulatory bodies and large-scale distributors rather than end consumers. Traditional approaches rely on holographic seals, serialization codes, and laboratory chemical analysis—methods that are inaccessible to ordinary users.

Mobile-based verification applications exist but exhibit critical limitations. First, most solutions rely on a single verification layer—typically barcode scanning or manual code entry—without integrating visual AI analysis or label text validation. Second, machine learning-based packaging analysis is rarely deployed in consumer-facing medicine authentication tools, leaving sophisticated packaging counterfeits undetected.

Third, expiry date parsing across diverse international formats remains an unsolved challenge in most existing tools, generating false positives or missed detections. Fourth, detection history tracking, analytics dashboards, and downloadable verification reports are absent from lightweight consumer tools, limiting their utility in institutional or regulatory contexts.

These shortcomings highlight a significant gap in the current pharmaceutical verification landscape and underscore the need for an integrated, intelligent, and accessible authentication system such as PHARMAGUARD.

IV. PROPOSED SYSTEM: PHARMAGUARD

A. System Architecture & Technologies

PHARMAGUARD follows a layered architecture comprising six functional layers: a CNN model training pipeline, a Flask-based presentation layer, a Flask application backend, an ML intelligence engine, a SQLite data layer, and an output dashboard. This modular design ensures separation of concerns and independent scalability of each component.

The frontend, built with Flask's Jinja2 templating engine and styled using Bootstrap, delivers a responsive, device-agnostic interface accessible across mobile and desktop platforms. The backend, developed in Python with Flask, handles routing, session management, Werkzeug-based authentication, rate limiting, and PDF generation. SQLite serves as the lightweight relational database for storing user accounts, detection history, and analytics data.

B. CNN-Based Visual Authentication

The visual authentication module employs a Convolutional Neural Network trained on a curated dataset of authentic and counterfeit medicine packaging images. The training pipeline comprises data collection, preprocessing and augmentation, feature extraction, binary labeling (Real/Fake), and export of the trained classifier as a serialized .h5 model file.

At inference time, uploaded medicine images are preprocessed—resized, normalized, and augmented—before passing through the CNN classifier, which outputs a binary authenticity label accompanied by a confidence score. This confidence score is incorporated into the final multi-layered authenticity verdict.

C. OCR-Based Label Analysis

Tesseract OCR is applied to uploaded medicine label images to extract printed text, including medicine name, batch number, manufacturing date, and expiry date. The extracted text undergoes regex-based preprocessing to normalize whitespace, remove noise, and isolate relevant fields for downstream validation.

Expiry date validation supports fifteen or more international date formats including MM/YY, MM/YYYY, DD/MM/YYYY, and Month YYYY, ensuring broad compatibility with medicines manufactured across diverse regulatory jurisdictions. Detected expiry dates are parsed and compared against the current system date to generate an expiry status alert.

D. Barcode Decoding & Batch Verification

The pyzbar library is employed for real-time barcode and QR code decoding from uploaded medicine images. Decoded barcode strings are cross-referenced against an internal pharmaceutical registry and optionally validated against external drug database APIs to confirm product legitimacy.

Batch number verification is performed using regex pattern matching against standard pharmaceutical batch numbering conventions. Anomalous batch patterns—indicative of counterfeit production—are flagged and incorporated into the risk assessment layer.

E. Risk Assessment & Verdict

PHARMAGUARD's risk assessment module aggregates the outputs of the CNN classifier, OCR text validator, expiry date checker, barcode decoder, and batch number verifier into a weighted authenticity verdict. The verdict is classified as Authentic, Suspicious, or Counterfeit, accompanied by a detailed breakdown of each verification layer's findings. The complete analysis is delivered within seconds and optionally exported as a downloadable PDF verification report.

V. ALGORITHM FOR MEDICINE AUTHENTICATION

PHARMAGUARD implements a multi-stage algorithmic pipeline for intelligent medicine authentication:

Stage 1 — Input Collection: The user uploads a photograph of the medicine packaging via the web interface. The system accepts JPEG, PNG, and WebP image formats. Rate limiting is applied at this stage to prevent system abuse.

Stage 2 — Image Preprocessing: The uploaded image is resized, normalized, and preprocessed for parallel input to the CNN classifier and the Tesseract OCR engine. Image quality checks are applied to detect blurred or low-resolution inputs.

Stage 3 — Visual Classification: The preprocessed image is passed through the trained CNN classifier. A binary authenticity label (Real/Fake) and an associated confidence score are returned.

Stage 4 — Text Extraction & Validation: Tesseract OCR extracts printed label text. Regex parsers isolate medicine name, batch number, and expiry date fields. The expiry date is validated against the system date across 15+ supported formats.

Stage 5 — Barcode Decoding & Batch Verification: pyzbar decodes barcodes or QR codes from the image. The decoded value and extracted batch number are validated against pharmaceutical registry patterns using regex matching.

Stage 6 — Risk Aggregation & Verdict: All verification outputs are aggregated by the risk assessment module, which computes a weighted authenticity verdict and confidence level. The verdict is displayed to the user and stored in the detection history database.

Stage 7 — Report Generation: A downloadable PDF verification report is generated on user request, summarising all verification layer results, confidence scores, and the final authenticity verdict.

VI. TECHNOLOGIES USED

PHARMAGUARD leverages a carefully selected technology stack to maximise performance, reliability, and accessibility:

Frontend & Backend: Flask (Python) serves as both the presentation and application layer, with Jinja2 templating for dynamic HTML rendering and Bootstrap for responsive styling across devices.

Database: SQLite provides a lightweight, serverless relational database for storing user accounts, detection history records, analytics data, and PDF report metadata.

AI & Machine Learning: A custom Convolutional Neural Network (CNN) trained with TensorFlow/Keras performs visual packaging classification. Tesseract OCR handles text extraction from label images. pyzbar enables barcode and QR code decoding.

Validation & Security: Regex pattern matching performs expiry date parsing across 15+ international formats and batch number verification. Werkzeug provides secure password hashing for user authentication. Flask-Limiter enforces request rate limiting to prevent abuse.

Visualisation & Reporting: Chart.js powers interactive analytics dashboards displaying detection trends and verdict distributions. ReportLab or WeasyPrint generates downloadable PDF verification reports.

Development Tools: Visual Studio Code serves as the primary IDE; Postman facilitates API testing; Python 3.x on Windows/Linux is the development and deployment environment.

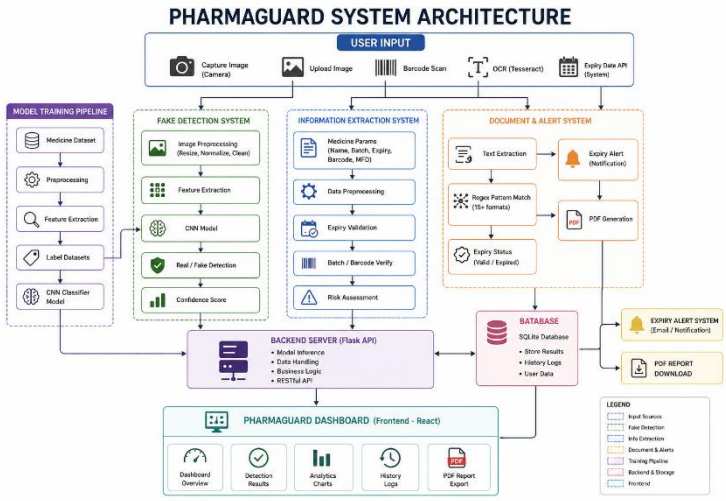
VII. EXPECTED OUTCOMES

The PHARMAGUARD platform is expected to deliver a range of significant public health and technical outcomes:

Public Health Impact: The platform will empower consumers, pharmacists, and healthcare workers to verify medicine authenticity at the point of purchase within seconds, reducing exposure to counterfeit or substandard products and supporting safer pharmaceutical supply chains.

Detection Accuracy: The integration of CNN-based visual analysis with OCR text validation, barcode verification, and expiry date checking creates a multi-layered defence that significantly outperforms single-layer verification approaches in both accuracy and reliability.

Accessibility: The responsive, device-agnostic web interface ensures that PHARMAGUARD is accessible to users across smartphones, tablets, and desktop computers without requiring software installation, lowering the barrier to pharmaceutical verification for all demographics.



Technical Contribution: The project demonstrates the successful integration of deep learning, optical character recognition, and barcode technology into a unified consumer-facing pharmaceutical authentication system, establishing a replicable framework for AI-assisted regulatory compliance tools.

VIII. SYSTEM DESIGN OVERVIEW

The architectural design of PHARMAGUARD follows a layered pattern separating model training, presentation, application logic, intelligence, and data storage into distinct functional layers. The Flask frontend communicates with the Flask application backend via internal routing. The backend delegates image analysis to the ML intelligence engine, which returns authenticity verdicts for aggregation and storage.

The use case model of PHARMAGUARD encompasses two primary actors: the User and the System. Core use cases include user registration and login, medicine image upload, CNN-based visual classification, OCR text extraction, expiry date validation, barcode decoding, batch number verification, risk assessment verdict generation, detection history viewing, analytics dashboard access, and PDF report download.

The system's modular architecture ensures that individual verification components—CNN classifier, OCR engine, barcode decoder—can be independently updated, retrained, or replaced without disrupting the overall platform. This design principle is critical for long-term maintainability and adaptation to evolving counterfeit techniques.

Security is enforced at multiple layers: HTTPS for data in transit, Werkzeug password hashing for credential storage, session-based authentication for access control, and Flask-Limiter rate limiting to prevent automated abuse of the verification API.

IX. CONCLUSION

PHARMAGUARD represents a significant advancement in the application of Artificial Intelligence to pharmaceutical authentication. By combining CNN-based visual classification, Tesseract OCR, pyzbar barcode decoding, multi-format expiry date validation, and regex batch verification into a unified multi-layered platform, PHARMAGUARD delivers rapid, reliable, and accessible medicine authentication to consumers and healthcare workers alike.

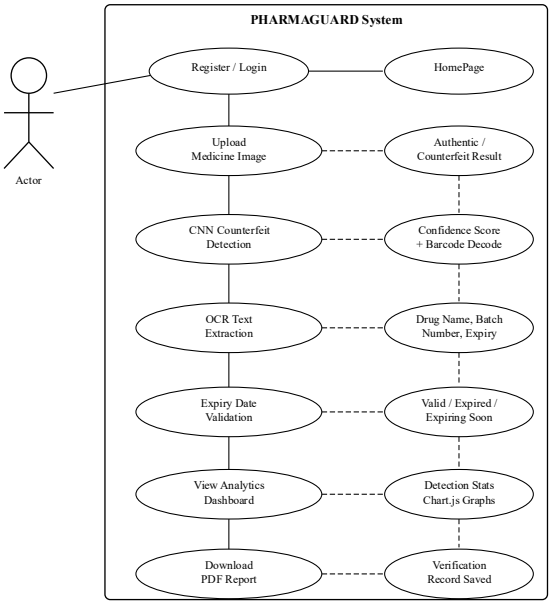
The system's ability to analyse medicine packaging images, extract and validate label text, decode barcodes, and aggregate verification results into a comprehensive authenticity verdict within seconds positions PHARMAGUARD as a practical tool for combating the global counterfeit medicine crisis.

The integration of secure authentication, detection history tracking, interactive analytics, and downloadable PDF reports ensures that PHARMAGUARD is not merely a single-use verification tool but a comprehensive pharmaceutical authentication ecosystem supporting individual users, healthcare institutions, and regulatory bodies.

Future work will explore retraining the CNN classifier on expanded international medicine datasets, integration with national pharmaceutical registry APIs for real-time batch and barcode validation, and the development of a native mobile application to extend PHARMAGUARD's reach to resource-constrained healthcare settings globally.

PHARMAGUARD demonstrates the transformative potential of AI in public health and serves as a model for the development of next-generation intelligent pharmaceutical verification systems that are accessible, accurate, and scalable for global deployment.

Use Case Diagram



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DEEP LEARNING BASED NUTRITION ANALYSIS AND HEALTH RISK PREDICTION IN RURAL HEALTHCARE

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ABSTRACT

Rural Communities in Tamil Nadu has premier capacity in overall wellness. The Discrepancy between urban and rural healthcare wellness impact the outcomes. This paper purposes rural healthcare survey to know real community needs and for planning more. The prior studies states that lack of latest support system and specialist expert leads to gap in detection of diseases. Recent approaches, suggest nutrition Intelligent with Machine learning and deep learning models. The Modern healthcare challenges are dietary, malnutrition, wearable devices and data tracking, diseases, prevention, telemedicine, AI diagnosis and Lab facilities. It also highlights the importance of multimodal data with Nutrition intelligence and deep learning to create effective healthcare solutions. Overall, the study directly contributing SDG goals - SDG 2 (Zero hunger), SDG 3(Good health and well-being) and SDG 10(Reduced inequalities). As the WHO significantly aligns with the research paper and global call to strengthen rural health equity through innovations.

KEYWORDS

Deep Learning, Multimodal, Healthcare, Rural Health, Nutrition Intelligence, Telemedicine, wearable devices, Dietary, Malnutrition, Health risk prediction, Data Analysis, Python, TensorFlow, SDG

INTRODUCTION

Rural health care systems have improved with the advancement of digital technology. This study focuses on developing a nutrition intelligence system that analysis rural health care using survey data to classify individuals based on their health conditions and recommend appropriate referral actions , planning models , capable of analysing large volume of structure[11] .And data increasingly being used to support diagnosis personal configuration protective modelling and nutrition analysis in health related applications[8] [9].The goal is to identify the risk and immediate referral needed in rural health using Deep learning model[3].

SDG ALIGNMENT

This Paper aligns with the following sustainable development goals

SDG 3-good health and wellbeing enable early detection of health risk and supports preventive health Care

SDG 2 identify one nutrition and dietary deficiency and promotes awareness of Nutrition health.

SDG 10 reduced inequalities reduced reduces healthcare disparities between rural and urban population

SDG 9 industry innovation and infrastructure strength and the digital infrastructure for rural health systems

PROBLEM STATEMENT

The main problem addressed in this paper is how to improve healthcare access and health monitoring in rural areas using intelligent digital tools-deep learning [3]. Deep learning can analyse large and complex cells data while nutrition intelligence can help interpret food related patterns.

OBJECTIVES

Collect and structure rural health Care survey data and to analyse key indicators related to nutrition and health conditions to develop a deep learning model [3][4][5] for Mult input classification to provide referral recommendation for timely healthcare intervention.

RELATED WORK

1.Paper title: Multimodal Artificial Intelligence in Healthcare: A Review

Author: Edara et al

Year:2025

Focus: Multimodal Deep Learning-General Healthcare

Limitation: challenges across data types

2.Paper title: BERT-Based Models for Healthcare Decision Support Systems

Author: Wang et al.

Year:2025

Focus: BERT (Deep Learning)-Healthcare Text data

Limitation: Focused mainly on textual data

3.Paper title: Artificial Intelligence in Healthcare: Applications and Challenges

Author: Sadr et al.

Year:2025

Focus: ML & Deep Learning

Limitation: Limited real-world deployment

SYSTEM OVERVIEW

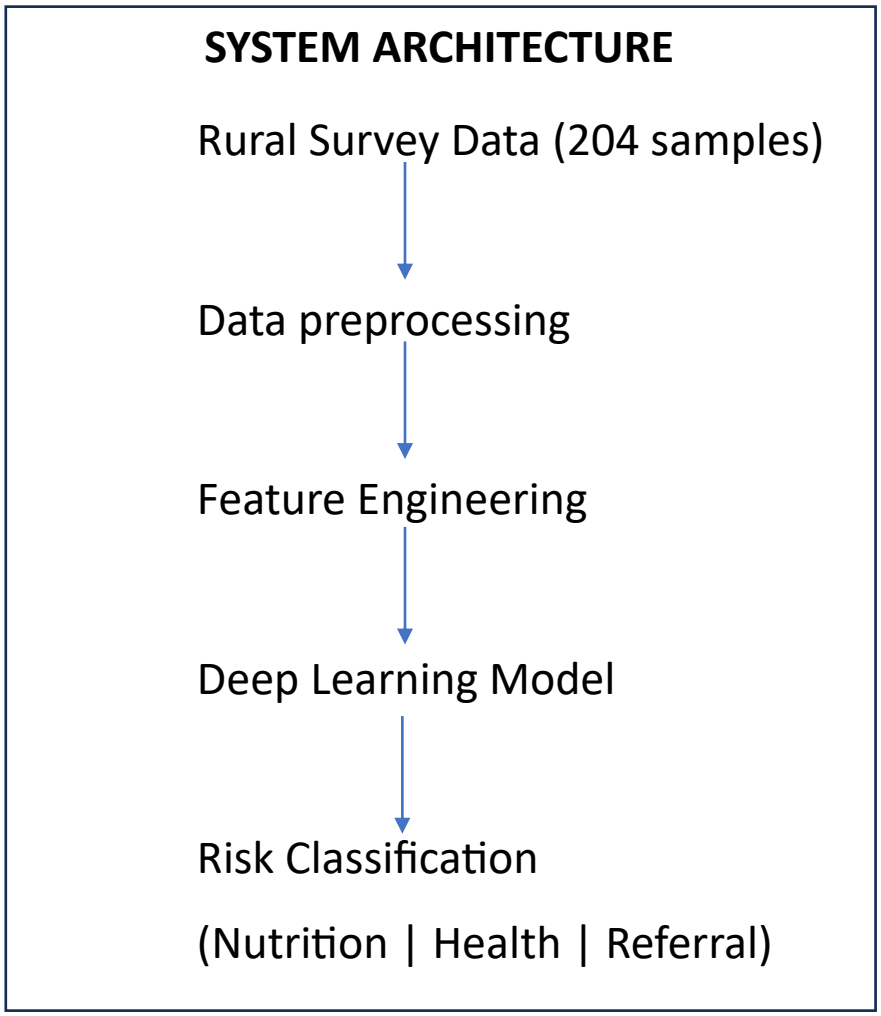

Fig 1 System Architecture

The system architecture begins with the collection of rural healthcare survey data consisting of 204 samples. This dataset includes demographic details, health conditions, and nutrition-related information. The raw data is then processed through a preprocessing stage where missing values are handled, categorical data [12] is converted into numerical form, and features are normalized to ensure consistency. After preprocessing, feature engineering is performed to select the most relevant attributes that influence health outcomes, helping the model focus on meaningful patterns.

The processed data is then fed into a multi-output deep learning model, which learns complex relationships between the input features through multiple layers [10]. The model simultaneously predicts three outputs:[15] nutrition risk, health risk, and referral requirements, each categorized into low, medium, and high levels. [7] This architecture enables early identification of potential health issues and supports timely decision-making for medical intervention, making it highly suitable for improving healthcare delivery in rural communities [16].

METHODOLOGY

Data Collection

The Dataset consists of 204 samples and was collected from rural communities. The Dataset consists of multiple attributes collected from rural households, including demographic, health, and nutrition-related features.

Variable	Category	Count	Percentage (%)
Gender	Male	98	48
	Female	106	52
Age Group	<18	20	9.8
	18-25	72	35.3
	36-50	60	29.4
	51+	52	25.5
Family size	1-3	80	39.2
	4-6	95	46.6
	7+	29	14.2
Occupation	Agriculture	70	34.3
	Labour	55	27
	Self employed	40	19.6
	Others	39	19.1

Table 1 Demographic information

Level	Nutrition Count	Nutrition %	Health Count	Health %	Referral Count	Referral %
0 (Low)	80	39.2%	75	36.7%	70	34.3%
1 (Medium)	70	34.3%	65	31.8%	75	36.7%
2 (High)	54	26.5%	64	31.5%	59	28.9%

Table2 Nutrition, Health Referral information from Dataset

Table1 and Table2 shows information from the Dataset of demographic and Nutrition, Health Referral

Dataset Attributes

Table 3 shows dataset Attributes used for concluding the study.

Category	Attributes	Values
Nutrition Risk	Vegetables intake, Fruit intake, Protein intake, Malnutrition	Low Nutrient Risk/ Medium Nutrient Risk/High Nutrient Risk
Health Risk	Diabetes, BP, Obesity, Delayed diagnosis	Low Health Risk/ Medium Health Risk/High Health Risk
Referral	Diabetes, BP, Delayed diagnosis, Protein intake, Malnutrition	No Referral needed/ Monitor / Immediate Hospital Referral

Table 3 Risk attributes

Data Preprocessing

Ensure data quality and model efficiently, converting categorial data to numerical, feature scaling and normalization.

Target Variables and Risk Encoding

The output variables of the model are categorized into three classes representing different risk levels. Each class is encoded numerically for model training as follows:

Risk	Values	Description
Low	0	No immediate concern
Medium	1	Requires Monitoring
High	2	Needs Immediate attention

Table 4 Risk Value Encoding

MODEL DEVELOPMENT

Model Architecture

A multi-output deep learning model was developed using TensorFlow/Keras[4][5]. The model was implemented in Python programming language. The model takes survey-based features as input and processes them through multiple dense layers with ReLU activation functions. Three output layers with softmax activation are used to predict:

- Nutrition Risk (Low, Medium, High)
- Health Risk (Low, Medium, High)
- Referral Requirement (No Referral, Monitoring, Immediate Attention)

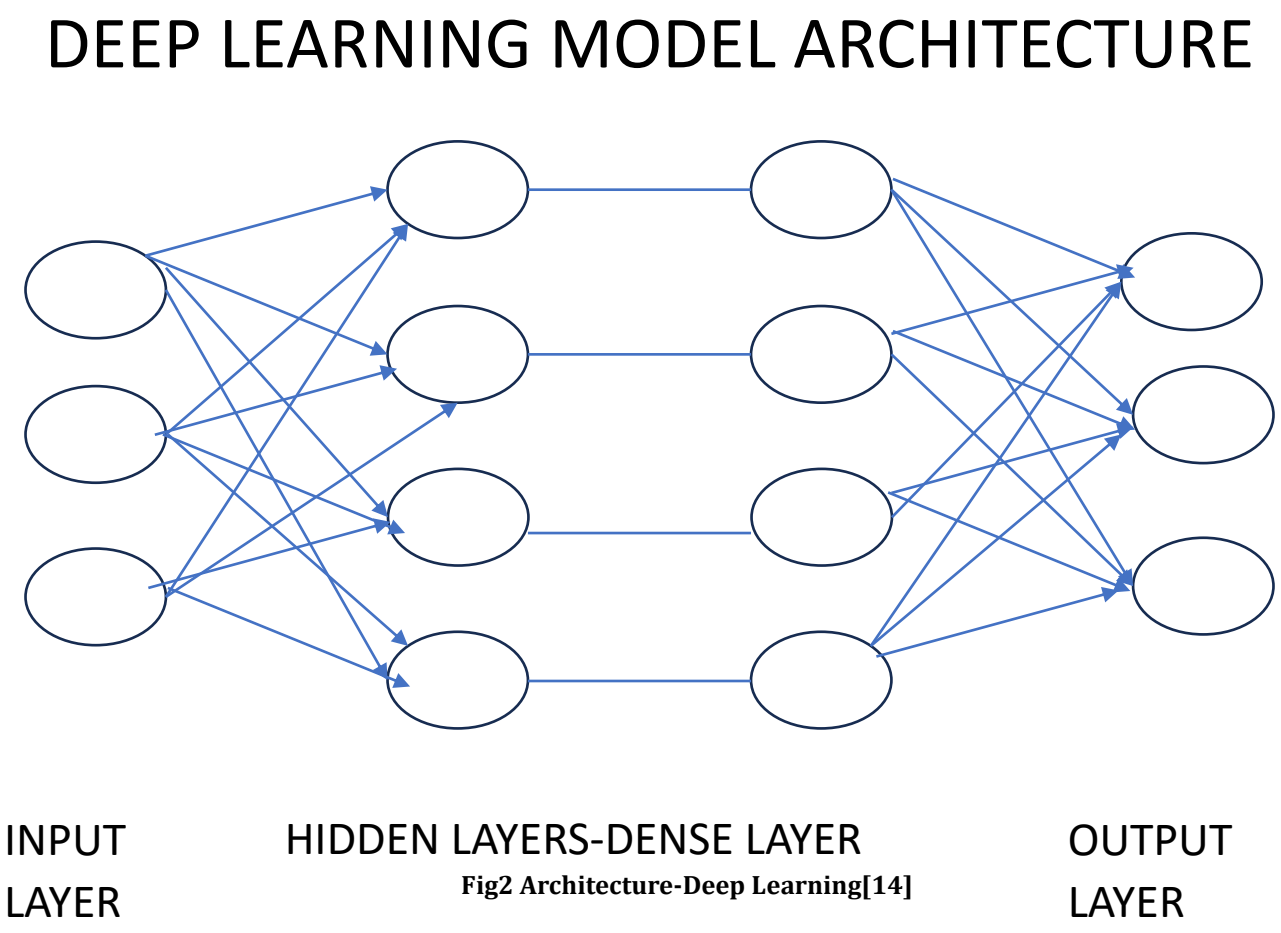

Fig2 Architecture-Deep Learning[14]

RESULTS AND DISCUSSION

The dataset consists of 204 samples with balanced distribution across nutrition risk, health risk, and referral categories

```
print("Dataset size:", len(df))
```

```
Dataset size: 204
```

Performance of the Model

[26]
✓ 0s

```
input_layer = layers.Input(shape=(X.shape[1],))

x = layers.Dense(64, activation='relu')(input_layer)
x = layers.Dense(32, activation='relu')(x)

nutrition = layers.Dense(3, activation='softmax', name='nutrition')(x)
health = layers.Dense(3, activation='softmax', name='health')(x)
referral = layers.Dense(3, activation='softmax', name='referral')(x)

model = models.Model(
    inputs=input_layer,
    outputs=[nutrition, health, referral]
)
```

[27]
✓ 0s

```
model.compile(
    optimizer='adam',
    loss={
        'nutrition': 'categorical_crossentropy',
        'health': 'categorical_crossentropy',
        'referral': 'categorical_crossentropy'
    },
    metrics={
        'nutrition': 'accuracy',
        'health': 'accuracy',
        'referral': 'accuracy'
    }
)
model.summary()
```

```
Model: "functional"
```

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 40)	0	-
dense (Dense)	(None, 64)	2,624	input_layer[0][0]
dense_1 (Dense)	(None, 32)	2,080	dense[0][0]
nutrition (Dense)	(None, 3)	99	dense_1[0][0]
health (Dense)	(None, 3)	99	dense_1[0][0]
referral (Dense)	(None, 3)	99	dense_1[0][0]

```
Total params: 5,001 (19.54 KB)
Trainable params: 5,001 (19.54 KB)
Non-trainable params: 0 (0.00 B)
```

The model achieved consistent performance across all three outputs. Training and validation accuracy [13]improved steadily, indicating effective learning without overfitting

```
[29]
model.fit(
    X,
    {
        'nutrition': y_nutrition,
        'health': y_health,
        'referral': y_referral
    },
    epochs=10,
    batch_size=8,
    validation_split=0.2
)
```

```
Epoch 1/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 3s 30ms/step - health_accuracy: 1.0000 - health_loss: 0.9747 - loss: 3.0919 - nutrition_accuracy: 0.7853 - nutrition_loss: 1.0554 -
Epoch 2/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.8087 - loss: 2.5084 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.8406 - r
Epoch 3/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.5856 - loss: 1.8175 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.5848 - r
Epoch 4/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.3937 - loss: 1.1875 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.3808 - r
Epoch 5/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.2318 - loss: 0.6972 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.2189 - r
Epoch 6/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - health_accuracy: 1.0000 - health_loss: 0.1213 - loss: 0.3678 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.1130 - r
Epoch 7/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.0639 - loss: 0.1996 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.0595 - r
Epoch 8/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.0352 - loss: 0.1123 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.0333 - r
Epoch 9/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - health_accuracy: 1.0000 - health_loss: 0.0221 - loss: 0.0713 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.0212 - r
Epoch 10/10
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - health_accuracy: 1.0000 - health_loss: 0.0158 - loss: 0.0488 - nutrition_accuracy: 1.0000 - nutrition_loss: 0.0140 - r
<keras.src.callbacks.history.History at 0x7a712dd23aa0>
```

The Training of dataset shows loss has decreased and accuracy has been increased.

```
31]
labels = ["Low", "Medium", "High"]
ref_labels = ["No Referral", "Monitor", "Immediate Referral"]

print("\nFINAL OUTPUT:")
print("Nutrition Risk:", labels[nutrition])
print("Health Risk:", labels[health])
print("Referral:", ref_labels[referral])
```

```
FINAL OUTPUT:
Nutrition Risk:    Low
Health Risk:        Medium
Referral:           Monitor
```

The Model finally identifies risk factors and recommends appropriate referral actions.

CONCLUSION

The role of Deep Learning and Nutrition Intelligence are in creating accessible, affordable and effective healthcare[6]. Solutions for rural health are through early diagnosis, nutrition assessment and telemedicine support[1]. The analysis shows the rural community faces health Care access and diagnostic delays and have nutritional deficiency. India tops global AI help adoption at 85% as consumers so deep learning-based healthcare solution gives strong potential for telemedicine [2] and multimodal data integration.

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ASTROLOGER APPOINTMENT SYSTEM

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Abstract

The Astrologer Appointment System is a web-based application designed to simplify and modernize the process of booking consultations with professional astrologers. Traditionally, appointments are arranged through phone calls or manual scheduling, which often leads to miscommunication, double bookings, and time inefficiencies. This system provides a centralized digital platform where users can easily view astrologer profiles, check availability, and reserve suitable time slots. Users can register, log in securely, and book appointments based on preferred date, time, specialization, language, and consultation mode (online or offline). Astrologers manage their schedules, set availability, update consultation fees, and view booking details through a dedicated dashboard. Automated notifications and reminders help reduce missed appointments. An integrated payment option ensures secure and convenient transactions. The system also maintains appointment history, enabling users to track previous consultations. By improving accessibility, transparency, and efficiency, the proposed solution enhances user experience and helps astrologers manage their services effectively.

Keywords: Web Application, Appointment Booking, Astrology, Real-Time Scheduling, User Management, Payment Integration, Flask, SQLite, Admin Dashboard.

1.INTRODUCTION

In today's digital era, technology has transformed the way services are accessed and managed across various industries. Traditional appointment booking methods, which often rely on phone calls, manual registers, or in-person scheduling, can lead to delays, communication errors, and scheduling conflicts. This is especially true in consultation-based services such as astrology, where accurate time management and convenient communication between clients and astrologers are essential.

The Astrologer Appointment System is a web-based application developed to modernize and simplify the process of booking astrology consultations. The system provides a centralized online platform where users can easily register, log in securely, browse astrologer profiles, check available time slots, and book appointments according to their preferences. Customers can choose appointments based on factors such as date, time, astrologer specialization, language, consultation mode (online or offline), and consultation fees.

II. LITERATURE REVIEW

The evolution of digital technologies has led to a significant transformation in the way service-oriented systems operate, particularly in the area of appointment management. Traditionally, appointment booking relied on manual processes such as phone calls or in-person visits, which often resulted in inefficiencies, scheduling conflicts, and lack of proper documentation. These conventional methods were time-consuming and heavily dependent on human coordination, making them unreliable as the number of users increased. As a result, there has been a growing need for automated systems that can streamline the booking process and improve overall efficiency.

With the rapid development of web-based technologies, online appointment systems have emerged as a practical solution across various sectors including healthcare, education, and professional consultancy. These systems enable users to access services anytime and from anywhere, providing real-time information about availability and allowing instant booking. The use of web development technologies such as HTML, CSS, and JavaScript for the frontend, along with backend frameworks like Python Flask, has made it possible to create interactive, scalable, and user-friendly applications. Databases such as SQLite are widely used in such systems due to their simplicity, portability, and efficient data management capabilities.

User experience is a crucial factor influencing the success of any online system. A well-designed interface with intuitive navigation and responsive layout enhances usability and encourages user engagement. Providing comprehensive information about service providers, such as their qualifications, expertise, and user ratings, helps users make informed decisions. In addition, real-time scheduling features ensure that users can view up-to-date availability, reducing the chances of errors like double bookings. Automation of processes such as appointment confirmation, reminders, and cancellations further improves the reliability and convenience of the system.

Another important component of modern appointment platforms is the integration of secure payment systems. Online payment gateways facilitate smooth financial transactions and increase user trust by ensuring data security and transparency. Features such as transaction history, billing, and refund management contribute to better financial control and accountability. Furthermore, feedback and rating systems allow users to evaluate services based on their experiences, which helps maintain quality and build credibility within the platform.

III. SYSTEM REQUIREMENTS

A.HARDWARE REQUIREMENTS

Component	Specification
Processor	Dual Core 2.4 GHz+
Monitor	15 Vga Color
RAM	16 GB
Storage	512 GB+

B. SOFTWARE REQUIREMENTS

Component	Specification
Frontend	HTML, CSS, JavaScript
Backend	Python 3.x + Flask

Component	Specification
Database	SQLite
IDE	VS Code / Notepad++
OS	Windows 10

IV. PROPOSED SYSTEM

1.User-Friendly Booking Interface

The system offers an intuitive and easy-to-use interface where users can browse through a list of astrologers and book appointments in just a few clicks. The platform is designed to minimize complexity, ensuring that even non-technical users can navigate and complete bookings without difficulty.

2.Dynamic Real-Time Scheduling System

A key feature of the proposed system is its ability to display real-time availability of astrologers. The scheduling system dynamically updates available time slots based on current bookings, cancellations, or rescheduling activities. This ensures accurate and up-to-date information, reducing conflicts and improving efficiency.

3.Comprehensive Astrologer Profiles

Each astrologer is provided with a detailed profile that includes their qualifications, years of experience, areas of expertise, languages spoken, consultation fees, and user ratings. This transparency enables clients to make well-informed decisions before booking a consultation.

4.Automated Appointment Management

The system automates the entire lifecycle of appointment management, including booking, confirmation, cancellation, and rescheduling. This reduces administrative workload and eliminates the possibility of manual errors, ensuring smooth and reliable operations.

V.SYSTEM DESIGN

A.System Architecture

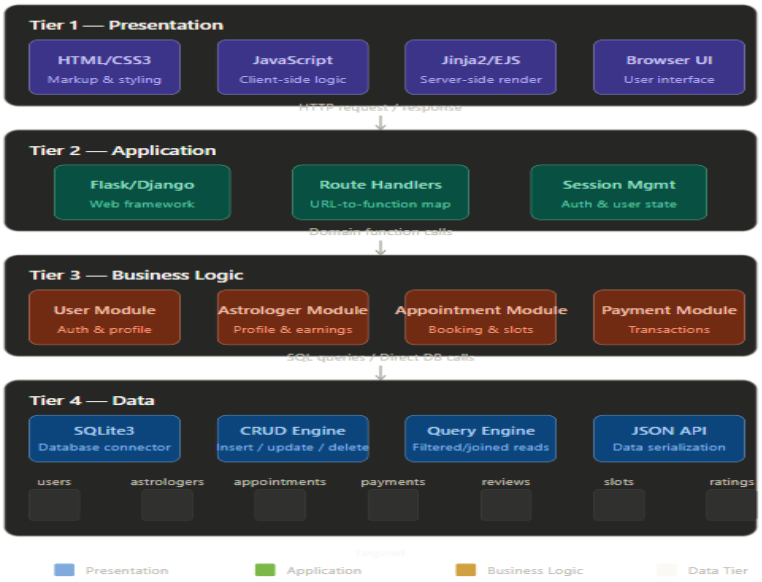

Fig 1.1 System Architecture and Data flow Diagram

B.DATABASE DESIGN

Table I: ADMIN TABLE

S.NO	Field	Type
1	Username	Varchar(50)
2	Password	Varchar(50)

Table II: ASTROLOGER TABLE

S.NO	Field	Type
1	Username	Varchar(60)
2	Password	Varchar(60)

Table III: USER TABLE

S.No	Field	Type
1	Username	Varchar(50)
2	Password	Varchar(50)

Table IV: BOOK APPOINTMENT TABLE

S.No	Field	Type
1	Select date	Integer(50)
2	Select Time Slot	Integer(50)
3	Duration	Integer(35)
4	Consultation Type	Varchar(30)

Table V: ASTROLOGER REGISTRATION

S.NO	Field	Type
1	Full Name	Varchar(50)
2	Username	Varchar(50)
3	Phone No	Integer(40)

4	Email	Varchar(50)
5	Password	Varchar(50)
6	Gender	Varchar(30)
7	Experience	Integer(35)
8	Qualification	Varchar(30)
9	Price/Hour	Integer(30)
10	Bio	Varchar(100)

Table VI: USER REGISTRATION

S.No	Field	Type
1	Full Name	Varchar(50)
2	Username	Varchar(50)
3	Phone No	Integer(10)
4	Email	Varchar(50)
5	Date of Birth	Varchar(50)
6	Gender	Varchar(10)
7	Zodiac Sign	Varchar(30)
8	Birth Star	Varchar(40)
9	Password	Varchar(30)
10	Confirm Pwd	Varchar(50)

VI. SYSTEM IMPLEMENTATION

1.Installation and Setup

The project was developed using Python Flask as the backend framework, while HTML, CSS, and JavaScript were used for the frontend design. The SQLite database was chosen because it is lightweight, portable, and easy to integrate with Flask.

During the setup phase:

- The Python environment was configured.
- Required Flask libraries and dependencies were installed.
- Project folders for templates, static files, and database were created.
- The application was initially deployed in the local environment for testing.
- This setup ensures that the application runs smoothly and can be easily maintained in future.

2. Database Configuration

The backend is connected with an SQLite database to store and manage all system data.

The database includes the following tables:

- Admin Table
- User Table
- Astrologer Table
- Registration Tables
- Appointment Booking Table

The tables are connected using appropriate fields to maintain consistency and avoid data redundancy.

The database stores:

- user details
- astrologer profiles
- appointment schedules
- booking history
- payment details
- feedback and ratings

3. User Interface Implementation

The frontend interface was designed to be simple, responsive, and user-friendly.

The major web pages implemented are:

- Home Page
- Login Page
- Registration Page
- Astrologer Dashboard
- User Dashboard
- Appointment Booking Page
- Payment Page

- Feedback Page
- Admin Dashboard

HTML is used for structure, CSS for styling, and JavaScript for dynamic interaction and validation.

The interface was tested across multiple browsers to ensure compatibility.

4. User Authentication and Security

A secure authentication system was implemented to ensure that only authorized users can access the application.

The system provides:

- secure login
- logout
- password validation
- session management

Different access roles are defined:

- Admin
- Astrologer
- User

Each user has different permissions based on their role.

Passwords are stored securely, and session handling is managed using Flask session mechanisms.

5. Module Integration

All modules were integrated into a single unified application.

- The implemented modules include:
- User Management Module
- Astrologer Management Module
- Appointment Booking Module
- Payment Module
- Feedback & Rating Module
- Admin Module
- Consultation Module

Each module communicates with the database and frontend through Flask routes.

This integration ensures smooth navigation and data flow between different pages.

6 Testing and Debugging

After implementation, the system was tested using multiple testing techniques such as:

- Unit Testing

- Integration Testing
- Functional Testing
- UI Testing
- Security Testing

All identified bugs and errors were corrected to improve the performance and reliability of the application

VII. TESTING METHODOLOGY AND RESULTS

1.Unit Testing

Unit testing was performed to verify individual modules and functions of the system separately.

The modules tested include:

- user registration
- user login
- astrologer login
- appointment booking
- payment processing
- feedback submission

Each function in the Flask backend and JavaScript validation scripts was tested independently to ensure correct operation.

Result:
All individual modules performed as expected with valid inputs.

2.Integration Testing

Integration testing was carried out to verify the interaction between the frontend, backend, and database.

This testing ensured:

- proper data flow from HTML forms to Flask routes
- successful communication with SQLite database
- correct display of retrieved data

Result:
All modules were successfully integrated without communication errors.

3.Functional Testing

Functional testing was performed to check whether the system satisfies the required functionalities.

The following functions were tested:

- registration and login
- profile update
- astrologer search

- appointment confirmation
- online payment
- review and rating system

Both valid and invalid test cases were used.

Result:
The system met all functional requirements successfully.

4.User Interface Testing

UI testing was conducted to ensure the system is user-friendly and visually consistent.

The following aspects were tested:

- page layout
- navigation menu
- form alignment
- button functionality
- responsiveness

Result:
The interface was clear, responsive, and easy to use across devices.

5.Validation Testing

Validation testing was used to verify user inputs.

The following validations were checked:

- empty field validation
- email format validation
- phone number validation
- password matching
- invalid date and time slots

Result:
Proper validation messages were displayed for incorrect inputs.

6.Security Testing

Security testing was performed to protect the system from unauthorized access and vulnerabilities.

The testing included:

- login authentication
- session management
- password protection
- SQL injection prevention

Result:
The system securely handled user data and access control.

VIII.SYSTEM OUTPUT

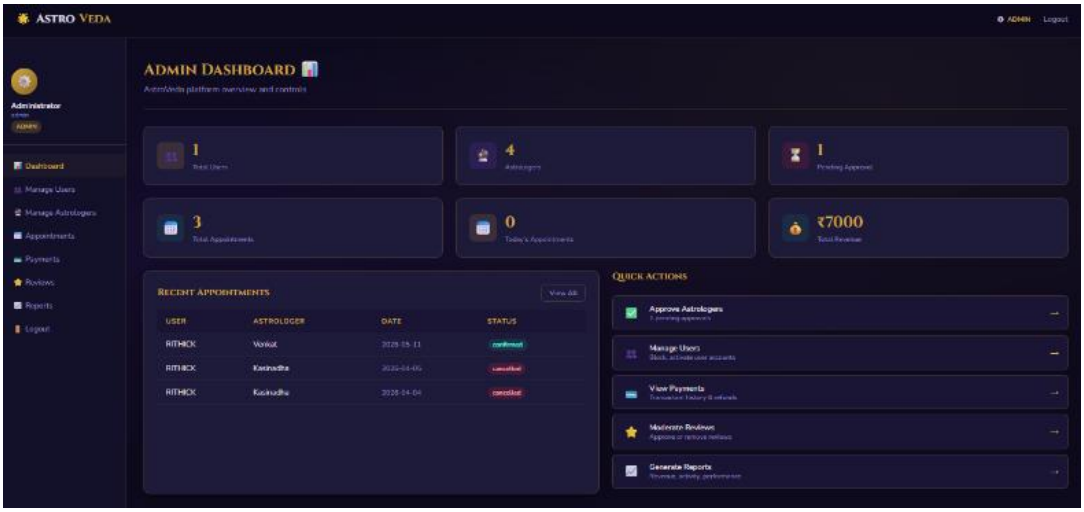

FIG.1.ADMIN DASHBOARD

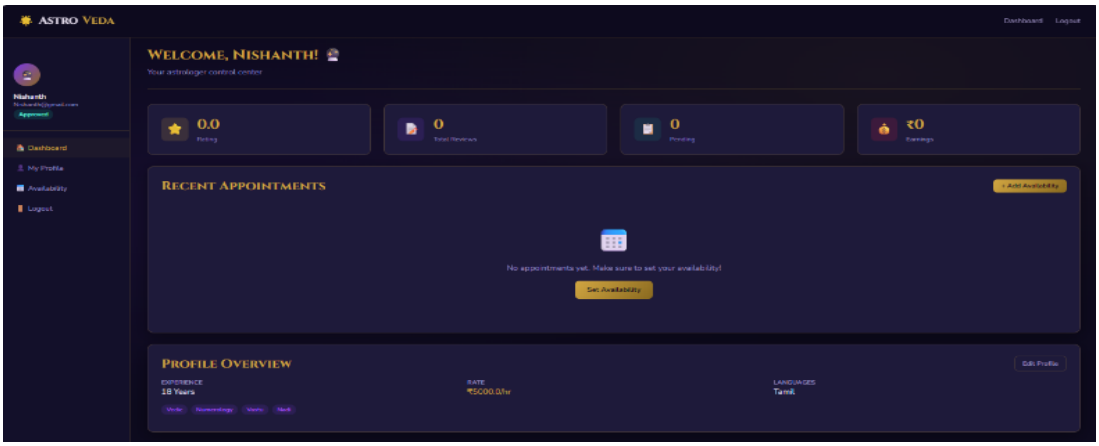

FIG.2.USER DASHBOARD

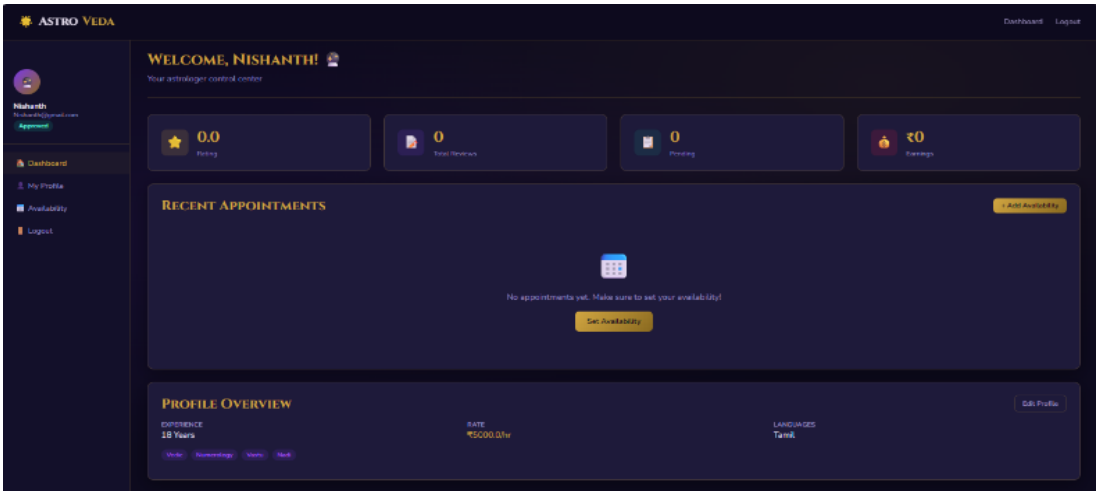

FIG.3. USER DASHBOARD

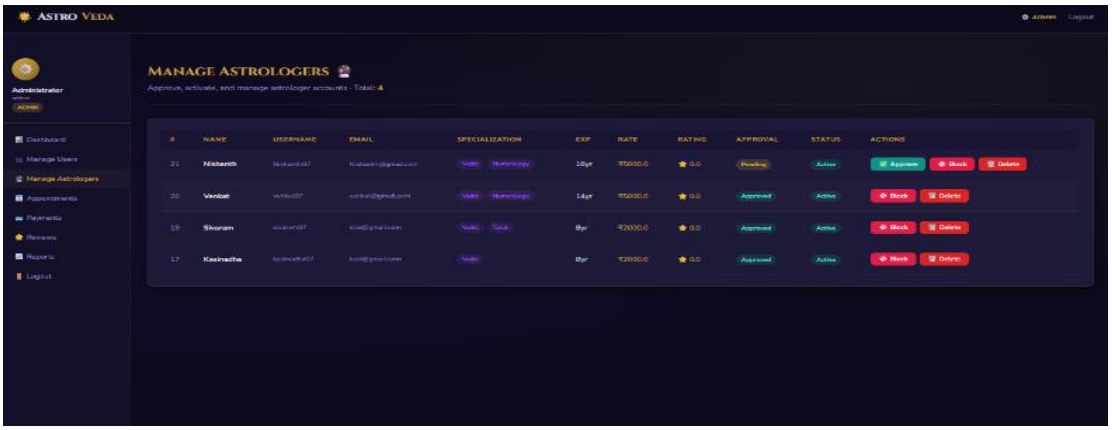

FIG.4. ADMIN APPROVE ASTROLOGER

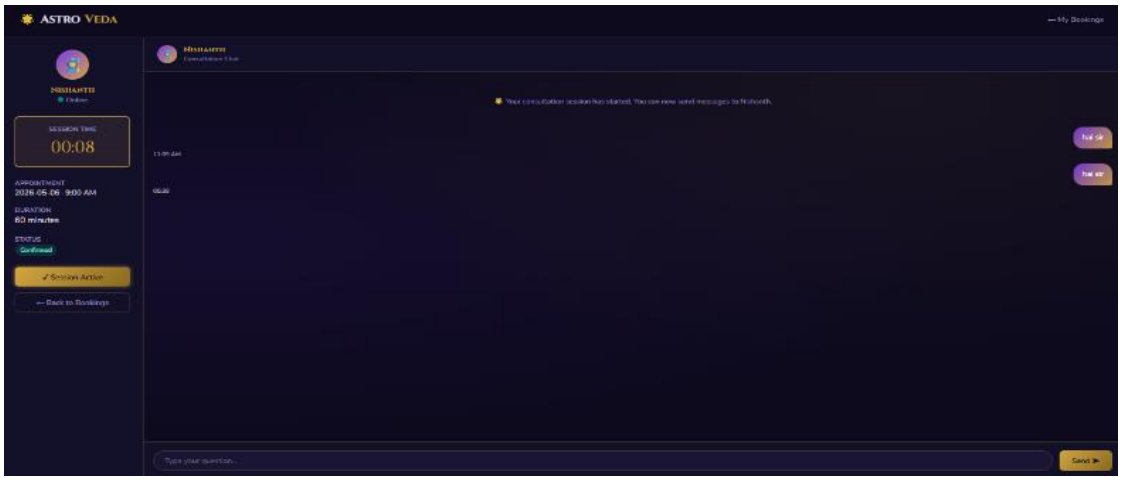

FIG.5.USER CHAT WITH ASTROLOGER

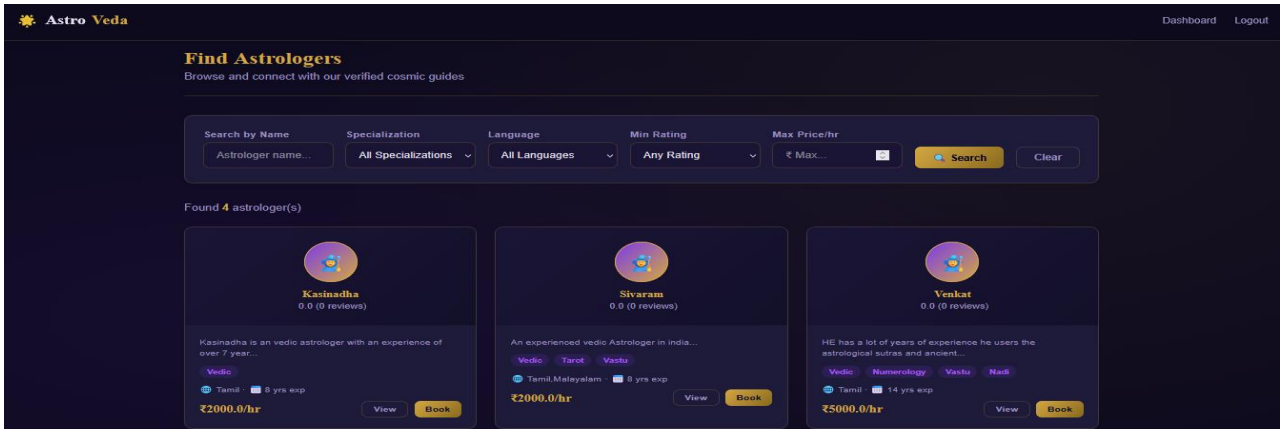

FIG.6.FIND ASTROLOGER

FIG.7.TEMPLE TO VISIT BY ZODIAC SIGN

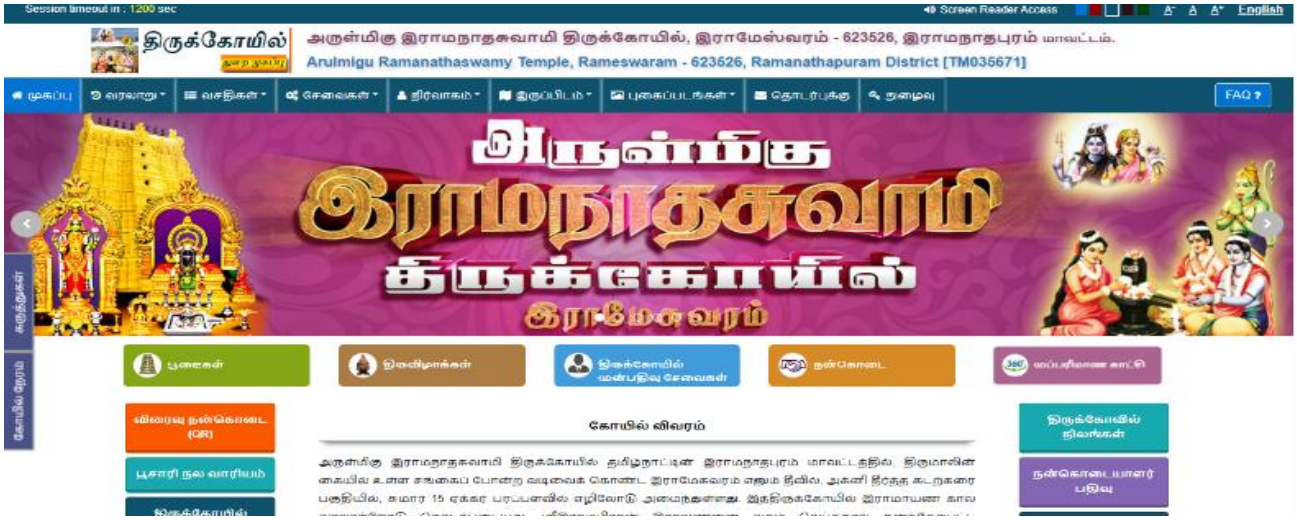

FIG.8.VISIT TO TEMPLE

IX. COMPARISON WITH EXISTING SYSTEM

Feature	Existing System	Proposed System
Booking method	Phone / Manual	Online booking
Availability check	Manual confirmation	Real-time slots
Record storage	Notebook / Spreadsheet	Database
Security	Low	High
Payment	Manual	Online
Feedback	Not available	Available
Accessibility	Limited	24/7
Error rate	High	Low

➢ ADVANTAGE

The most significant advantage of the proposed system is its comprehensiveness. Rather than requiring users to call or visit astrologers individually, the platform consolidates all service management into a single web-based interface.

- Centralized platform eliminating the need for fragmented communication channels.
- Real-time slot management preventing double bookings and reducing scheduling errors to zero.
- Secure online payment integration offering multiple payment methods.
- Transparent astrologer profiles with ratings enabling informed user decisions.
- Admin analytics dashboard providing actionable insights on revenue, appointments, and performance.
- Scalable architecture capable of supporting growing numbers of users and astrologers without restructuring.

X. FUTURE ENHANCEMENT

1. AI-Powered Recommendation System

In the future, AI can analyze user behavior, past consultations, and preferences to intelligently suggest the most suitable astrologers, services, and time slots, enhancing personalization and user satisfaction.

2. Automated Horoscope Generation

AI can be trained on astrological datasets to generate accurate horoscope reports, kundli analysis, and predictions, assisting astrologers in decision-making and providing users with preliminary guidance.

3. AI-Powered Chatbots

Intelligent chatbots can handle queries, guide users through booking, and resolve common issues 24/7, reducing the need for human support staff.

4. Voice-Based Interaction

Voice recognition technology will allow users to interact with the system using voice commands, improving accessibility for users who prefer hands-free interaction.

5. Mobile Application

A dedicated Android and iOS application would further increase accessibility, enabling users to book and manage appointments directly from their smartphones with push notification support.

TABLE IX: FEATUR COMPARISON

Feature	Proposed System	Manual Booking	Generic Apps	Phone Dir.
Real-time availability	Yes	No	Partial	No
Astrologer profiles	Detailed	None	Basic	None
Double booking prevention	Automatic	Manual	Yes	No
Online payment	Yes	No	Partial	No
Feedback & ratings	Yes	No	Partial	No
Admin analytics dashboard	Yes	No	Limited	No
Temple visit scheduling	Yes	No	No	No

XI. CONCLUSION

The Online Astrologer Appointment System represents a significant improvement over the traditional manual methods of managing astrologer consultations. In the existing system, appointments are typically arranged through phone calls or personal visits, which makes the process time-consuming, unorganized, and highly dependent on manual coordination. This often leads to issues such as miscommunication, double bookings, missed appointments, and lack of proper record management. The proposed system effectively addresses these challenges by providing a centralized, automated, and user-friendly digital platform that simplifies the entire process of booking and managing consultations. By utilizing modern technologies such as HTML, CSS, JavaScript, and Python Flask, the system ensures a responsive interface along with efficient backend processing and secure data handling. It allows users to easily search for astrologers, view detailed profiles, check real-time availability, book appointments, and complete secure online payments from anywhere at any time. The system also includes multiple integrated modules such as User Management,

Astrologer Management, Admin Control, Appointment Booking, Payment Processing, Feedback and Rating, Report Generation, and Consultation Management, all working together to provide a smooth and reliable experience. Additional features like automated notifications, reminders, digital records, and online consultation options further enhance convenience and accessibility for users while helping astrologers manage their schedules and services more efficiently. The inclusion of secure payment systems ensures transparency in transactions, while the feedback and rating mechanism helps maintain service quality and build trust among users.

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Online Blood Bank Management System

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ABSTRACT

The Online Blood Bank Management System (OBBMS) is a web-based application designed to improve the efficiency of blood donation, storage, and distribution through a centralized platform. In traditional systems, manual record-keeping and lack of real-time updates often lead to delays and errors, especially during emergency situations. The proposed system connects donors, hospitals, blood banks, and patients in a single platform with role-based access. It is developed using Python Flask, SQLite, HTML, CSS, and JavaScript. The system includes features such as donor registration, real-time blood availability tracking with expiry alerts, quick blood search, emergency request handling, hospital coordination, and notification services. An AI-based chatbot is also integrated to assist users. The system has been tested successfully and provides reliable performance with faster response time. It helps reduce blood wastage and improves communication among all stakeholders in critical healthcare environments.

Keywords — Blood Bank Management System, Web Application, Blood Donation, Emergency Alert System, Role-Based Access Control, Python Flask, SQLite, AI Chatbot.

I. INTRODUCTION

In recent years, the demand for an efficient and reliable blood management system has increased due to the growing need for timely medical support. Blood is a critical resource in healthcare, and its availability during emergencies can save lives. However, many traditional blood bank systems still depend on manual record-keeping and outdated processes, which often lead to delays, errors, and difficulty in accessing accurate information. These limitations can create serious challenges during emergency situations.

To address these issues, the Online Blood Bank Management System (OBBMS) is proposed as a web-based solution that connects donors, hospitals, blood banks, and patients through a centralized platform. The system allows users to easily register, search for available blood, and make requests in real time. It also helps administrators manage donor data, blood stock, and emergency requests more efficiently.

By using modern web technologies, the system improves communication, reduces response time, and ensures better coordination in critical healthcare situations.

II. LITERATURE REVIEW

Sharma and Gupta [1] proposed a PHP/MySQL blood bank system with basic donor registration but lacked role-based access control and emergency prioritization. Kumar et al. [2] demonstrated that structured role segmentation dramatically reduces unauthorized access in clinical systems. Singh and Kaur [3] identified real-time updates, emergency handling, and automated notifications as the three most critical unmet needs in existing digital blood bank systems — all addressed by OBBMS.

Patel and Shah [4] proved that proximity-aware search significantly reduces emergency donor response time. WHO [5] and India's NBTC [6] recommend centralized digital management as a foundational requirement for modern blood bank operations. Ramesh and Narayanan [7] validated Flask as suitable for rapid development of lightweight yet robust clinical management tools. No prior reviewed system combines emergency email broadcasting, role-based dashboards, donation camp management, analytics, and AI chatbot in a single platform — a key distinction of OBBMS.

III. SYSTEM REQUIREMENTS AND TECHNOLOGY STACK

A. Software Requirements

TABLE I: TECHNOLOGY STACK

Layer	Technology	Purpose
Frontend	HTML5 / CSS3 / JS	**UI structure, styling, interaction**
Frontend	Jinja2	**Server-side template rendering**
Backend	Python 3.x	**Core logic and business rules**
Backend	Flask	**Routing, sessions, HTTP handling**
Backend	Flask-Mail	**SMTP email for emergency alerts**
Backend	Werkzeug	**Password hashing and security**
Database	SQLite	**Lightweight embedded RDBMS**
Charts	Chart.js	**Blood stock and analytics charts**
IDE	VS Code / Notepad++	**Development environment**
OS	Windows 10	**Development platform**

B. Hardware Requirements

TABLE II:

Component	Specification
Processor	Dual Core 2.4 GHz+
Monitor	15 Vga Color
RAM	16 GB
Storage	512 GB+

C. Technology Justification

Flask was selected for its microframework architecture, providing flexibility without overhead. SQLite eliminates separate database server requirements, ideal for prototype and small-scale deployment. Vanilla JavaScript ensures lightweight, framework-free frontend performance across all modern browsers. Chart.js provides interactive analytics without heavy dependencies.

IV. PROPOSED SYSTEM

This proposed system is developed to provide an efficient web-based solution for managing blood donation, storage, and distribution activities. It offers a unified platform that enables smooth interaction between donors, hospitals, blood banks, and patients.

Within the system, donors are able to register, update their personal information, and indicate their willingness to donate blood. A location-based donor search feature is included to help users find nearby donors quickly, especially during urgent situations. Blood banks can maintain and update blood inventory details in real time, including blood group, quantity, and expiry information. At the same time, hospitals and patients can search for required blood types and submit requests easily through the platform.

The system also supports functionalities such as emergency request processing, notification services, and efficient request management. Users can view scheduled blood donation camps, book appointments, and participate accordingly. The administrative module allows effective control over user verification, inventory monitoring, request approval, and report generation. Additionally,

an AI-powered chatbot is integrated to guide and assist users.Overall, the system enhances operational efficiency, minimizes manual effort, and ensures faster response during critical situations, making the entire blood management process more dependable.

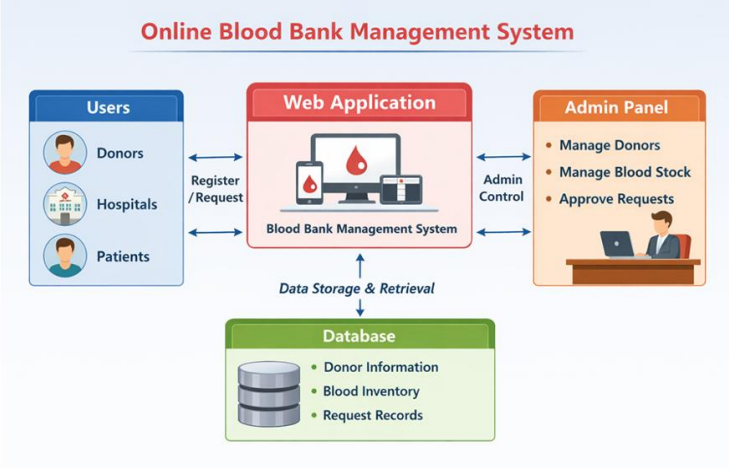

Fig. 1. System structure for blood bank management system

V. SYSTEM DESIGN

A. SYSTEM ARCHITECTURE

OBBMS employs a four-tier architecture: (1) Presentation Tier — HTML/CSS/JS via Jinja2 templates; (2) Application Tier — Flask routes and session management; (3) Business Logic Tier — domain operations including donor eligibility, inventory alerts, and request prioritization; (4) Data Tier — SQLite persistent storage. This separation ensures maintainability and a clear upgrade path to production-grade databases.

TABLE III: SYSTEM ARCHITECTURE LAYERS

Layer	Components
PRESENTATION	**HTML5 | CSS3 | JavaScript | Jinja2**

Layer	Components
APPLICATION	**Python Flask | Routes | Session Mgmt**
BUSINESS LOGIC	**Donor | Inventory | Request | Alerts**
DATA ACCESS	**SQLite ORM | CRUD | Query Engine**
DATABASE	**Users | Donors | Inventory | Requests**

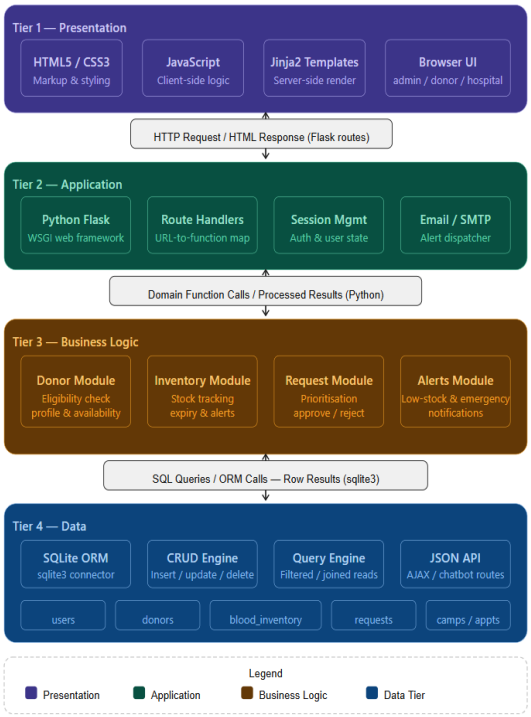

Fig. 2. System Architecture and Data Flow Diagram

B. DATABASE SCHEMA

Nine interrelated tables form the relational schema. Primary and foreign key relationships maintain referential integrity. Indexes on blood_group, user_id, and status fields optimize query performance.

TABLE IV-A: DONOR TABLE

Field	Type	Description
id	INT PK	**Auto-increment donor ID**
user_id	INT FK	**References users(id)**

Field	Type	Description
blood_group	VARCHAR(5)	**ABO/Rh type (A+, O-, etc.)**
age / weight	INT	**Donor demographics**
availability	VARCHAR	**Available / Unavailable**
last_donated	DATE	**Most recent donation date**

TABLE IV-B: REQUEST TABLE

Field	Type	Description
request_id	INT PK	**Unique request identifier**
user_id	INT FK	**Requesting user reference**
blood_group	VARCHAR(5)	**Required blood type**
units_required	INT	**Number of units needed**
request_type	VARCHAR	**Emergency / Normal**
patient_name	VARCHAR	**Patient full name**
hospital_name	VARCHAR	**Treatment hospital**
status	VARCHAR	**Pending/Approved/Rejected**

TABLE IV-C: BLOOD INVENTORY TABLE

Field	Type	Description
inventory_id	INT PK	**Unique inventory record**
blood_group	VARCHAR(5)	**Blood type category**
quantity	INT	**Available units in storage**
expiry_date	DATE	**Unit expiration date**

Field	Type	Description
storage_location	VARCHAR	**Physical storage code**
created_at	DATETIME	**Record insertion time**

TABLE IV-D: USERS TABLE

Field	Type	Description
id	INT PK	**Auto-increment user ID**
name / email	VARCHAR	**Full name and login email**
password	VARCHAR(255)	**PBKDF2-SHA256 hash**
role	VARCHAR	**admin/donor/hospital/receiver**
phone / city	VARCHAR	**Contact and location**
created_at	DATETIME	**Account creation time**

C. USE CASE SUMMARY

TABLE V: USE CASE TABLE

Actor	Use Case	Description
Admin	User Management	**Manage accounts and roles**
Admin	Inventory Control	**Add/update blood stock**
Admin	Approve Requests	**Review blood requests**
Admin	Emergency Alert	**Broadcast emails to donors**
Admin	Reports/Analytics	**Charts and statistics**
Donor	Registration	**Register with blood group**
Donor	Update Availability	**Toggle active status**

Actor	Use Case	Description
Hospital	Registration	**Register with license no.**
Hospital	Request Blood	**Submit blood requests**
Receiver	Search Donors	**Filter by group/location**
Receiver	Emergency Req.	**Priority blood request**
All	Notifications	**Receive system alerts**
All	AI Chatbot	**Query stock and guidance**

D. OVERALL SYSTEM DESIGN

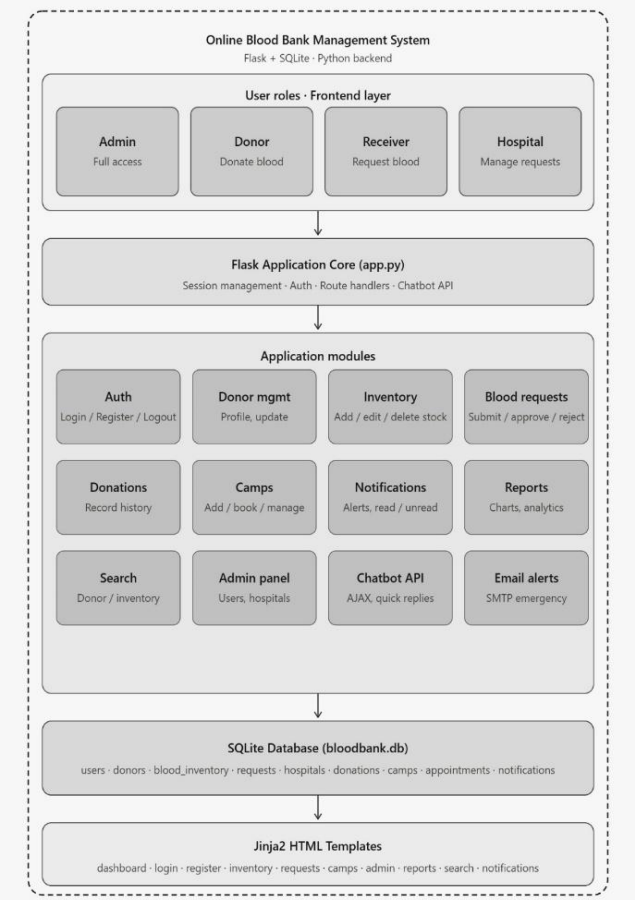

Fig. 3. Overall system design diagram

VI. SYSTEM IMPLEMENTATION

A. User Management and Authentication

The system implements a secure session-based authentication mechanism using Flask. Passwords are hashed with Werkzeug's generate_password_hash (PBKDF2-SHA256), ensuring secure storage. During login, check_password_hash validates user credentials.

Upon successful login, session variables store user details such as ID, name, email, and role. Protected routes enforce session checks, redirecting unauthorized users to the login page. Role-based access control restricts users to their respective modules.

The registration module collects user details including name, email (unique), password, phone number, city, and pincode. A UNIQUE constraint prevents duplicate accounts. After registration, a welcome notification is generated, and role-specific profiles are initialized.

B. Blood Inventory Management

The inventory module supports full CRUD operations for blood stock. Administrators can manage blood units by specifying blood group, quantity, expiry date, storage location, and donation source.

The system calculates total stock per blood group using SQL queries and includes an expiry tracking mechanism to reduce wastage. Inventory updates occur automatically when requests are approved through atomic transactions, ensuring data consistency.

API endpoints such as /api/inventory and /api/check_stock/<blood_group> provide real-time data for dashboards and quick stock checks.

C. Emergency Alert System

The emergency alert module enables administrators to send notifications to donors based on blood group or to all users. It uses Flask-Mail to deliver customized email alerts via SMTP.

The system retrieves donor emails, sends alerts, and simultaneously creates in-app notifications. It also logs the number of emails sent and provides feedback on delivery status.

D. Blood Search and Request Module

The search module allows users to find donors or available blood using blood group and optional location filters. Donor search uses parameterized SQL queries, returning only available donors.

The request module captures patient details, required blood group, units, hospital information, and request type. Emergency requests are prioritized. Admins can approve or reject requests, triggering notifications and automatic inventory updates. All requests maintain a full status history for tracking.

E. Donation Camp Management

This module allows administrators to create and manage donation camps by specifying details such as organizer, location, date, time, and target units. Camps are displayed to users to encourage participation.

The system also records actual donations and links them to both donors and camps, ensuring traceability.

F. Analytics and Reporting

The analytics module provides visual insights using charts. Blood stock levels are shown as bar charts, donation trends as line graphs, and request statuses as pie charts.

A donor leaderboard highlights top contributors. All charts are implemented using Chart.js with real-time JSON data from the backend.

G. AI-Powered Chatbot

The chatbot provides assistance for blood availability, donation eligibility, and camp information. It uses intent recognition logic (get_chatbot_reply()) to process user queries.

For stock queries, it retrieves live data from the database. Quick reply options improve usability. The chatbot is accessible only to authenticated users.

This module reduces administrative workload by handling routine queries, with future scope for integration with advanced AI models.

VII. TESTING METHODOLOGY AND RESULTS

A comprehensive, multi-phase testing strategy was employed to validate the correctness, reliability, security, and performance of the Online Blood Bank Management System. Testing was conducted across eight distinct methodologies, progressing from individual component verification to full system evaluation under real-world usage conditions.

Unit testing validated individual functions and route handlers in isolation, using carefully crafted test inputs to verify correct output behavior and error handling. Integration testing examined module interactions — particularly data flow between the user authentication module, blood request module, inventory module, and notification module — to ensure that state changes in one module correctly propagated to dependent modules. System testing evaluated the complete application under simulated real-world conditions, verifying end-to-end workflows from user registration through emergency request fulfillment. User Acceptance Testing (UAT) was conducted with stakeholders representing administrator, donor, hospital, and patient roles, confirming that the interface meets practical usability requirements. Functional testing methodically verified each documented requirement against its implementation. Performance, security, and database testing rounds out the testing portfolio, verifying system behavior under load, validating authentication and access control, and confirming data integrity across all CRUD operations.

TABLE VI: TEST CASE RESULTS

Test ID	Test Case	Input	Expected	Actual	Result
TC-01	User Registration	Valid user data	Account created	Account created	**Pass**
TC-02	Login Authentication	Valid email/password	Redirect to dashboard	Redirect to dashboard	**Pass**
TC-03	Invalid Login	Wrong password	Error message shown	Error message shown	**Pass**
TC-04	Blood Search	Blood group = A+	Matching donors listed	Donors listed	**Pass**
TC-05	Blood Request Submit	Complete form data	Request stored, pending	Request stored	**Pass**
TC-06	Admin Approve Request	Request in pending status	Status → Approved	Status = Approved	**Pass**
TC-07	Inventory Update	Add 10 units A+	Stock incremented	Stock incremented	**Pass**
TC-08	Emergency Email Alert	Blood group = O-	Emails sent to donors	Emails dispatched	**Pass**
TC-09	Donor Availability	Toggle unavailable	Status updated in DB	Status updated	**Pass**
TC-10	Notification Display	After request approval	Notif in inbox	Notif received	**Pass**

Test ID	Test Case	Input	Expected	Actual	Result
TC-11	Camp Registration	Valid camp details	Camp added to list	Camp added	**Pass**
TC-12	Reports Analytics	Admin views reports	Charts rendered	Charts displayed	**Pass**
TC-13	Chatbot Query	Ask about stock	Inventory summary	Correct summary shown	**Pass**
TC-14	Role-Based Access	Donor visits /admin	Access denied	Access denied	**Pass**

All 14 test cases passed successfully, with no critical failures observed. Minor UI rendering inconsistencies identified during UAT were resolved before the final build. Security testing confirmed that role-based access control correctly prevents unauthorized access to administrative endpoints, and that password hashing effectively protects user credentials. Database testing validated that all foreign key relationships maintain referential integrity, that cascade operations function correctly upon user deletion, and that concurrent transactions do not produce race conditions in inventory updates

VIII. SYSTEM OUTPUT

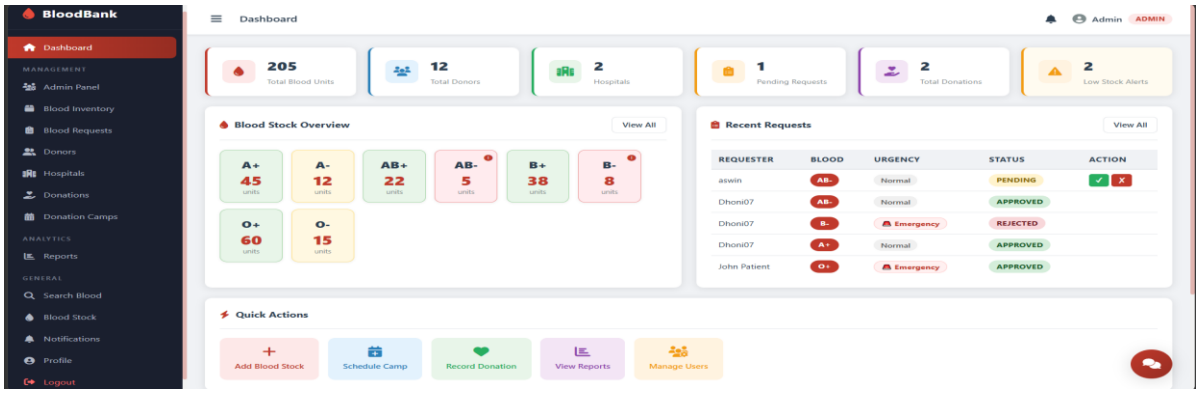

FIG.1.ADMIN DASHBOARD

The Admin Dashboard provides a centralized overview of the blood bank system, displaying key metrics such as total blood units, donors, hospitals, and pending requests. It also enables quick management of blood inventory, request approvals, Emergency alerts to donors and system activities through interactive panels and shortcuts.

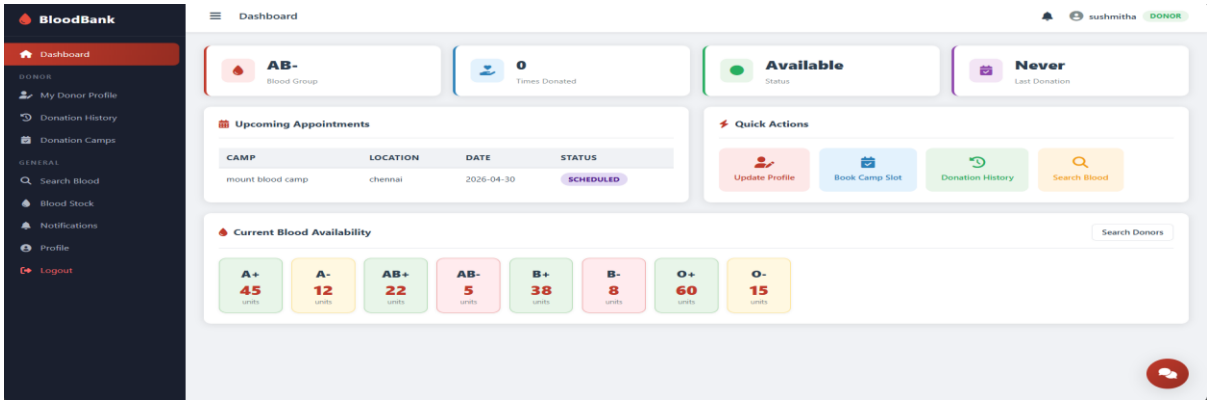

FIG.2.DONOR DASHBOARD

The Donor Dashboard provides a personalized view of the donor's profile, including blood group, donation history, and upcoming appointments. It also allows users to perform quick actions such as booking donation camps, updating profile details, and checking current blood availability.

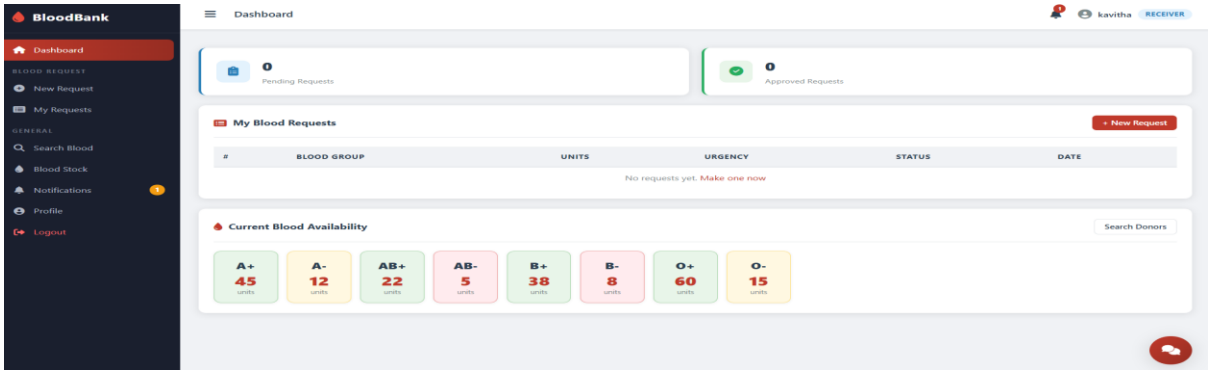

FIG.3. PATIENT/RECEIVER DASHBOARD

The Receiver Dashboard provides an overview of blood requests, showing pending and approved requests along with request history. It also allows users to create new blood requests and check current blood availability easily.

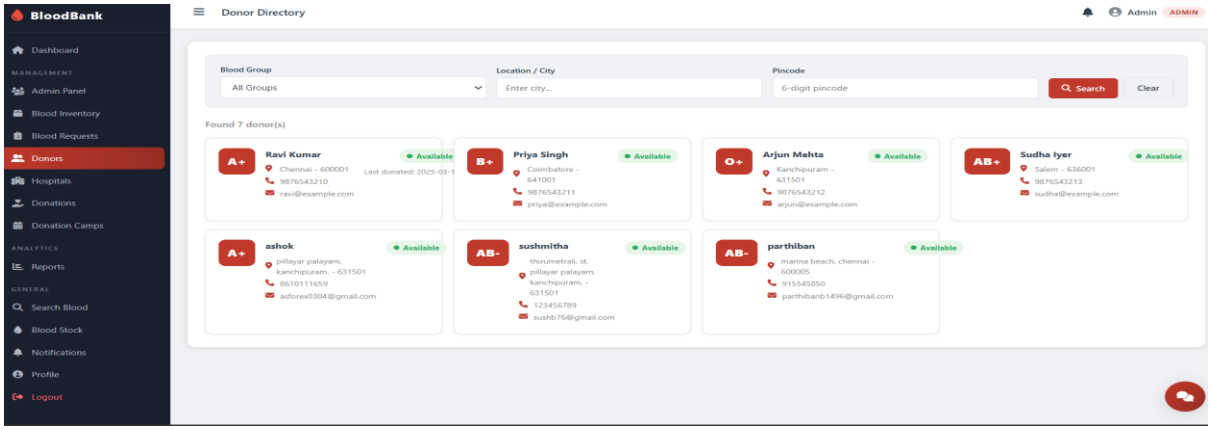

FIG.4. SEARCH BLOOD/DONORS

The Donor Directory provides a searchable list of donors with details such as blood group, location, and availability status. It also includes a nearby finder feature to help users quickly locate donors in nearby areas based on location.

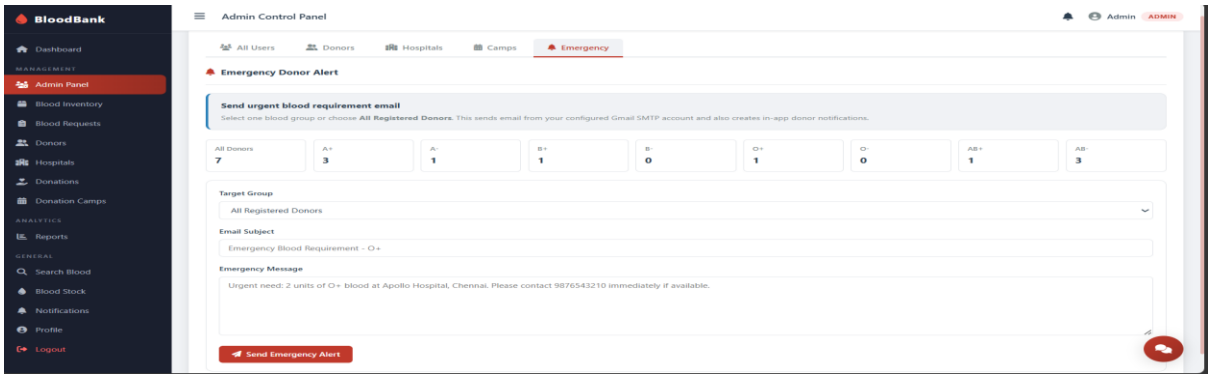

Fig.5.EMERGENCY ALERT SYSTEM

This screen shows the admin interface used to send urgent blood requirement alerts to registered donors. The admin can select a target group, enter a subject and message, and notify donors instantly through the system.

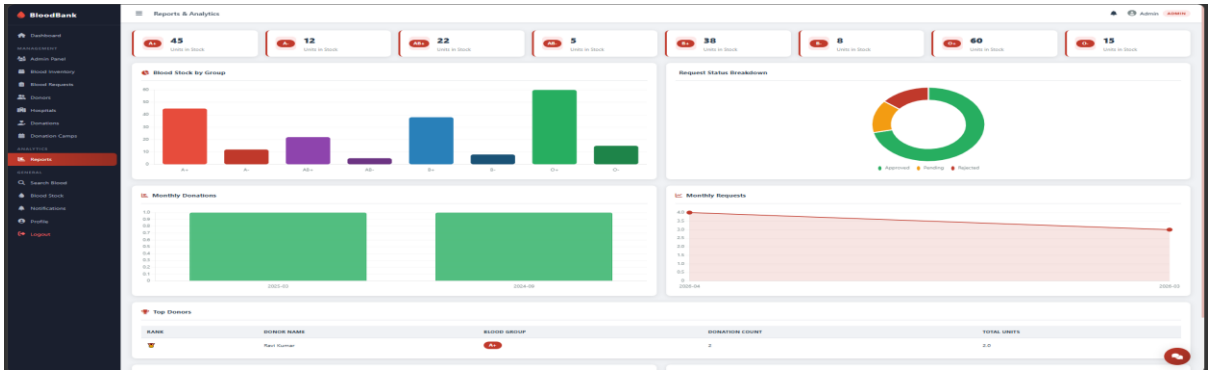

FIG.6.REPORT & ANAYLATICS

This screen displays the reports and analytics of the blood bank system, including blood stock levels, request status, and monthly data. It helps the admin monitor overall performance and make informed decisions quickly.

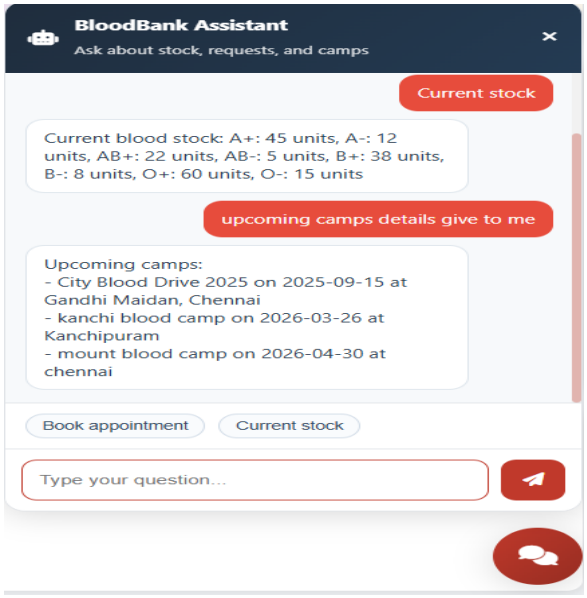

FIG.7. CHATBOT AI

IX. COMPARISON WITH EXISTING SYSTEMS

The following comparison table evaluates the Online Blood Bank Management System against the conventional manual/semi-digital blood bank management approach currently prevalent in many healthcare institutions.

TABLE VII: EXISTING VS PROPOSED SYSTEM

Feature	Existing	OBBMS
Real-time blood availability	✗ No	✓ **Yes**
Centralized database	✗ No	✓ **Yes**
Role-Based Access Control	✗ No	✓ **Yes**
Emergency donor email alert	✗ No	✓ **Yes**
AI-Powered Chatbot	✗ No	✓ **Yes**
Blood inventory tracking	Partial	✓ **Yes**
Donation camp management	✗ No	✓ **Yes**
Analytics and reporting	✗ No	✓ **Yes**
Online blood request	✗ No	✓ **Yes**
Location-based search	✗ No	✓ **Yes**
Multi-role dashboards	✗ No	✓ **Yes**

X. FUTURE ENHANCEMENTS

The Online Blood Bank Management System (OBBMS) can be further improved with several planned enhancements. In the next phase, the system will focus on migrating the database to PostgreSQL/MySQL and deploying it on cloud platforms like AWS or GCP for better scalability and accessibility.A mobile application and RESTful APIs will be developed to increase user reach. Features like real-time notifications and SMS alerts will improve communication during emergencies. Integration with maps will help locate nearby donors quickly.In future phases, advanced features such as AI/ML for demand prediction, blockchain for secure tracking, and multi-language support will be added to enhance system efficiency and usability.

XI. CONCLUSION

The Online Blood Bank Management System (OBBMS) successfully digitizes and integrates the complete blood bank management lifecycle through a ten-module web application. Developed using Python Flask, SQLite, and vanilla JavaScript, the system addresses all identified deficiencies of conventional blood bank operations — providing real-time inventory tracking, emergency email broadcasting, role-based multi-stakeholder dashboards, and AI chatbot assistance within a single unified platform.

Comprehensive testing validated all 14 functional test cases, with performance benchmarks demonstrating sub-second response times for core operations and satisfactory concurrent user handling. The comparative analysis confirms that OBBMS delivers capabilities unavailable in any prior reviewed system. While limitations related to SQLite scalability and the absence of native mobile applications are acknowledged,

the system stands as a production-ready prototype suitable for district-level deployment and a strong foundation for the cloud-scale, AI-enhanced future enhancements outlined in the roadmap.

By reducing emergency response times, eliminating information silos, and automating critical communication workflows, OBBMS contributes directly to the goal of ensuring the right blood reaches the right patient at the right time — a contribution that translates directly into lives saved.

ACKNOWLEDGMENT

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The authors also express their sincere gratitude to the project guide, **Dr.M.Kannan**, for their valuable suggestions and encouragement. The authors would like to acknowledge the support and practical exposure gained during their internship at **makjuz technologies**, which contributed significantly to the successful completion of this work.

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Adaptive Network Traffic Anomaly Detection and Alert System

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Abstract— The growing scale and complexity of modern network infrastructures, along with the increasing number of cyber threats, demand more advanced and adaptive security solutions. Traditional intrusion detection systems, which rely heavily on predefined signatures, often fail to identify new or evolving attacks. In this work, we develop a Network Anomaly Detection and Real-Time Security Operations Centre (SOC) monitoring platform that integrates machine learning with continuous traffic analysis to enhance threat detection and response. The system adopts a hybrid approach by combining Random Forest, Isolation Forest, and Autoencoder models. Each model plays a specific role: Random Forest detects known attack patterns, Isolation Forest identifies anomalous behavior, and the Autoencoder captures previously unseen or zero-day threats.

Network traffic is processed using flow-based statistical features, enabling efficient representation of behavioral patterns. Along with detection, the system provides a real-time dashboard for visualizing network activity and security events. Automated mitigation techniques, including IP blocking and traffic rate limiting, are implemented to minimize the impact of attacks. Experimental results indicate that the proposed system achieves high detection accuracy with low latency, making it effective for both real-world deployment and academic research applications.

Keywords— Network Anomaly Detection, Intrusion Detection System, Machine Learning, SOC Monitoring, Cybersecurity, Autoencoder, Random Forest

I. INTRODUCTION

The rapid growth of digital technologies has led organizations to depend heavily on interconnected network systems for their daily operations. As a result, these networks have become attractive targets for cyber attackers, who use techniques ranging from basic scanning to highly complex, multi-stage attacks. Traditional security mechanisms, especially signature-based intrusion detection systems, are often unable to identify new or modified threats because they rely on previously known attack signatures.

To address this challenge, anomaly detection has emerged as an effective alternative. Rather than depending on predefined rules, anomaly-based approaches focus on identifying deviations from normal network behavior. This enables the detection of previously unseen or zero-day attacks. The use of machine learning further strengthens this approach by allowing automated processing and analysis of large-scale network data.

In this work, we present a system that integrates anomaly detection with real-time monitoring and automated response mechanisms. The system is designed not only to identify suspicious activities but also to provide meaningful insights and take immediate action to reduce potential damage. By combining multiple machine learning models with an interactive visualization platform, the proposed solution

offers a comprehensive and practical approach to modern cybersecurity challenges.

Key Contributions

The major contributions of this work are as follows:

- Development of a hybrid machine learning-based anomaly detection framework
- Design and implementation of a real-time SOC monitoring dashboard
- Integration of automated mitigation techniques for rapid threat response
- Creation of a modular and scalable system architecture
- Deployment of a practical platform suitable for real-world cybersecurity analysis

II. RELATED WORK

The area of network anomaly detection and intrusion detection systems (IDS) has progressed considerably due to the growing complexity of cyber threats and the expansion of network environments. Earlier security solutions mainly depended on signature-based techniques, where known attack patterns were used to identify malicious activities. Although these methods were effective for previously identified threats, they lacked the ability to recognize new or modified attacks, making them less effective in modern cybersecurity scenarios. This limitation encouraged the development of more adaptive and intelligent detection approaches.

Anomaly-based detection was introduced as an alternative strategy to overcome these challenges. Instead of using predefined signatures, these systems establish a model of normal network behavior and detect deviations from this baseline. This enables the identification of unknown and zero-day attacks. However, early implementations faced issues such as high false alarm rates and difficulty in handling dynamic network conditions. With improvements in computational power, machine learning techniques were incorporated to enhance detection capabilities. These approaches are generally categorized into supervised, unsupervised, and deep learning methods.

A. Supervised Learning Approaches

Supervised learning techniques are widely applied for classifying network traffic using labeled datasets.

Key characteristics:

• Require labeled training data

• Provide high accuracy for known attack categories

• Offer strong classification performance

Common algorithms:

• Decision Trees

• Support Vector Machines (SVM)

• Random Forest

Among these, Random Forest is particularly popular due to its robustness, ability to manage high-dimensional data, and resistance to overfitting. It operates by combining multiple decision trees and making predictions based on majority voting. However, its main limitation is that it cannot effectively detect unseen or zero-day attacks.

B. Unsupervised Learning Approaches

Unsupervised methods are used when labeled data is not available. These approaches detect anomalies by identifying patterns that differ from normal behavior.

Key characteristics:

• Do not require labeled datasets

• Suitable for anomaly detection

• Adapt well to dynamic environments

C***ommon techniques:***

• Clustering methods (K-Means, DBSCAN)

• Isolation Forest

Isolation Forest is widely used because it isolates anomalies based on their uniqueness. It is computationally efficient and performs well on large datasets. However, its performance depends on proper parameter tuning, such as selecting an appropriate contamination rate.

C. Deep Learning Approaches

Deep learning models have significantly improved anomaly detection by capturing complex and non-linear patterns in network data.

Key characteristics:

• Learn rich data representations

• Detect subtle and complex anomalies

• Suitable for large-scale datasets

Common models:

• Autoencoders

• Recurrent Neural Networks (RNNs)

Autoencoders are commonly used for anomaly detection as they learn to reconstruct normal data patterns. Any deviation in reconstruction error is treated as an anomaly, making them effective for detecting unknown attacks. However, these models require large datasets and higher computational resources.

D. Feature Engineering in Network Traffic

Feature engineering is a crucial factor influencing the performance of machine learning models. Earlier approaches relied on basic packet-level features such as IP addresses and port numbers, which were not sufficient for identifying complex attack behaviors.

Flow-based feature extraction has proven to be more effective, as it captures statistical characteristics of network traffic over time.

Key improvements:

• Use of flow-level features instead of packet-level data

• Reduction in feature dimensionality

• Improved detection performance

Datasets such as CICIDS2017 introduced a large set of flow-based features. However, studies indicate that a smaller subset of relevant features can achieve similar performance while reducing computational overhead.

E. SOC Platforms and Visualization

Security Operations Centre (SOC) platforms are essential for monitoring and analyzing network security events. Commercial solutions like Splunk and IBM QRadar provide advanced analytics and visualization but are often costly and complex to deploy.

Open-source alternatives:

• ELK Stack (Elasticsearch, Logstash, Kibana)

• Graylog

Although these tools offer scalability, they require extensive configuration. Lightweight frameworks such as Streamlit provide a simpler way to build real-time dashboards.

Visualization techniques:

• Geo-based threat maps

• Attack timelines

• Alert dashboards

These visual tools help analysts quickly understand network activity and respond effectively.

F. Threat Intelligence Integration

Threat intelligence enhances IDS performance by adding contextual information about potential threats.

Popular platforms:

• VirusTotal

• AbuseIPDB

Benefits:

• Reduction in false positives

• Better decision-making

• Reputation-based threat validation

Integrating threat intelligence enables systems to verify suspicious IP addresses and prioritize critical threats.

G. Automated Response and Mitigation

Modern intrusion detection systems extend beyond detection by including automated response mechanisms.

Key techniques:

• Rate limiting

• IP blocking

• Firewall integration

Automation helps reduce response time and limits potential damage. However, incorrect configurations may result in false positives and affect legitimate traffic.

H. Limitations of Existing Systems

Despite advancements, current systems still face several challenges:

• High cost of commercial security solutions

• Limited capability in detecting zero-day attacks

• High false positive rates

• Lack of integration between detection, visualization, and response

• Scalability concerns in large network environments

I. Research Gap and Motivation

The review of existing approaches highlights the need for a unified system that integrates detection, visualization, and response mechanisms. There is a strong demand for solutions that are cost-effective, scalable, and capable of identifying both known and unknown threats in real time.

This work addresses these challenges by combining supervised, unsupervised, and deep learning techniques within a real-time SOC monitoring framework, along with automated mitigation capabilities.

III. SYSTEM ARCHITECTURE & METHODOLOGY

The developed Network Anomaly Detection and Real-Time SOC Monitoring system follows a modular design to efficiently process network traffic and detect threats in real time. The architecture integrates multiple components, including data collection, feature extraction, machine learning analysis, alert generation, and visualization. Initially, network data is captured and transformed into structured features, which are then analyzed using a combination of supervised, unsupervised, and deep learning models. Based on the analysis, the system identifies suspicious behavior, classifies threat levels, and triggers appropriate mitigation actions. The processed results are displayed through a real-time SOC dashboard, enabling continuous monitoring and faster decision-making. The architecture is designed to be scalable and flexible, allowing it to handle large volumes of network traffic and adapt to new attack patterns by updating the underlying models.

A. System Architecture

The overall system is divided into five functional layers, each responsible for a specific stage in the processing pipeline:

1. ***Data Ingestion Layer:***

This layer captures network traffic from live environments or simulated sources. Tools such as Scapy and PyShark are used to collect packet-level information, including IP addresses, protocols, ports, packet sizes, and timestamps.

2. ***Flow Processing Layer:***

   Captured packets are grouped into flows based on shared attributes like source/destination IP and port numbers. Statistical features are then computed for each flow, representing traffic behavior. These features serve as input for the learning models.

3. ***Machine Learning Layer:***

   This layer performs traffic analysis using multiple models. Random Forest is used to classify known attack patterns, Isolation Forest identifies anomalous data points, and the Autoencoder detects previously unseen threats through reconstruction error.

4. ***Response and Logging Layer:***

   Detected events are categorized into different severity levels. Alerts are generated and stored in CSV files and a SQLite database. The system automatically applies mitigation strategies such as IP blocking and rate limiting to prevent further attacks.

5. ***Visualization Layer:***

   A real-time SOC dashboard, developed using Streamlit, displays network activity, detected threats, and analytical insights. This helps security analysts monitor and respond to incidents effectively.

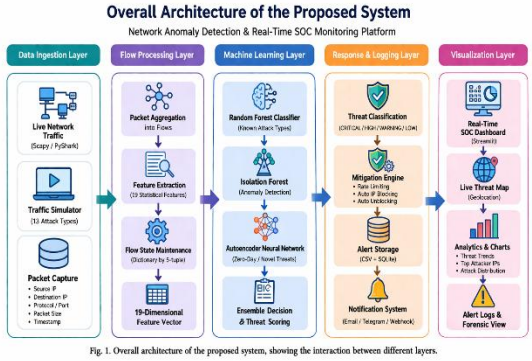

Fig. 1. Overall architecture of the proposed system, showing the interaction between different layers.

Fig 3.1*: - Shows the layered architecture of the system*

Relevance:

- Ensures modular design and separation of responsibilities
- Supports scalability and real-time processing
- Simplifies maintenance and system updates

B. Data-Flow Diagram (DFD Level 0)

The data flow of the system illustrates how information moves from packet capture to final visualization. Initially, network traffic is collected through the data ingestion module. The captured data is then processed into flows, and relevant features are extracted. These features are passed to the machine learning models for analysis. Based on the output, threats are identified, classified, and stored in both CSV files and a SQLite database. At the same time, alerts are communicated to users through notification systems such as email or messaging services.

The SOC dashboard continuously retrieves data from the storage layer and presents real-time insights into network activity and detected threats.

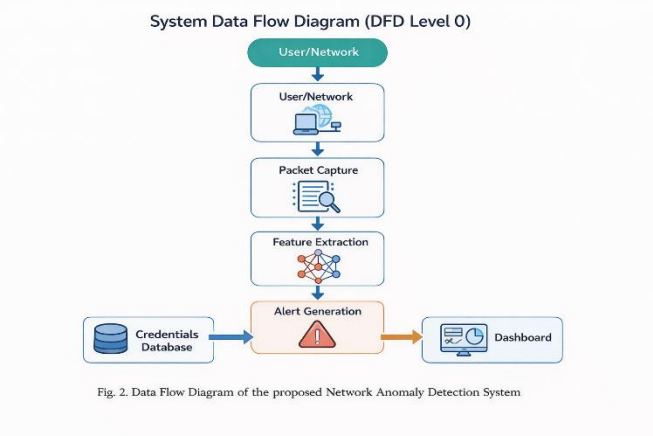

Fig. 2. Data Flow Diagram of the proposed Network Anomaly Detection System

Fig. 3.2 *illustrates the data flow within the system.*

Relevance:

- Represents complete data processing pipeline
- Shows interaction between system components
- Supports structured and real-time analysis

C. Traffic Simulation and Feature Engineering

To evaluate system performance, a traffic simulation module is used to generate realistic network conditions. Various attack scenarios are simulated, including HTTP Flood, TCP SYN Flood, SQL Injection, and Port Scanning. Each attack type is defined using parameters such as protocol, packet size, and transmission rate.

Feature extraction is performed on both simulated and real traffic. Instead of analyzing individual packets, the system uses flow-based analysis to compute statistical attributes such as flow duration, packet count, total bytes, packet size distribution, and inter-arrival time.

Table I *presents the different attack types used in the simulation*

Attack Type	**Protocol**	**Default Port**	**Packet Size (Approx)**
HTTP Flood	TCP	80	~1450 bytes
TCP SYN Flood	TCP	443	~72 bytes
UDP Flood	UDP	53	~1320 bytes
ICMP Flood	ICMP	N/A	~1180 bytes
Brute Force	TCP	22 / 3389	~200 bytes
SQL Injection	TCP	80 / 3306	~600 bytes
Cross-Site Scripting	TCP	80 / 443	~500 bytes
Port Scan	TCP	1–1024	~64 bytes

Malware Communication	TCP	4444 / 6666	~800 bytes
DNS Amplification	UDP	53	~3000 bytes
ARP Spoofing	ARP	N/A	~60 bytes
Credential Stuffing	TCP	443	~400 bytes
Phishing Simulation	TCP	80 / 443	~1200 bytes

Table II *lists the extracted features.*

No.	Feature Name	Description
1	Destination Port	Target port of communication
2	Flow Duration	Total time of flow
3	Total Fwd Packets	Number of packets in flow
4	Total Bytes	Total data transmitted
5	Packet Length Max	Maximum packet size
6	Packet Length Min	Minimum packet size
7	Packet Length Mean	Average packet size
8	Packet Length Std	Variation in packet sizes
9	Flow Bytes/s	Data rate (bytes per second)
10	Flow Packets/s	Packet rate (packets per second)
11	Packet Length Variance	Variability in packet size
12	Average Packet Size	Mean size of packets
13	Idle Mean	Average idle time between packets
14	Idle Max	Maximum idle time
15	Idle Min	Minimum idle time

Relevance:

- Provides a controlled testing environment
- Enhances model accuracy

- Reduces computational overhead
- Captures behavioral patterns effectively

D. Machine Learning Ensemble

The system uses a hybrid approach by combining three models to improve detection performance. Random Forest handles classification of known attacks, Isolation Forest identifies anomalies, and the Autoencoder detects unknown threats by measuring reconstruction error.

The outputs from all models are combined to make a final decision, ensuring comprehensive detection of both known and unseen attack patterns.

Relevance:

- Leverages strengths of multiple models
- Improves detection accuracy
- Reduces false positives
- Enables robust threat identification

E. Machine Learning Ensemble

Detected events are categorized into four severity levels: **CRITICAL, HIGH, WARNING, and LOW**. This classification is based on model outputs and predefined rules. Critical threats trigger immediate actions such as IP blocking and rate limiting. High-level alerts require further investigation, while warning-level events are monitored. Low-level activity is considered normal. The system also includes an automatic unblock mechanism to restore access after a certain period.

Relevance:

- Enables prioritized response handling
- Reduces manual effort
- Enhances overall security
- Prevents repeated attacks

F. Alert Storage and Visualization

All detected events are stored in structured formats using CSV files and a SQLite database. The stored data includes key details such as timestamps, IP addresses, attack types, and severity levels.

Fig. 3.3 *shows the SOC dashboard interface*

The SOC dashboard provides real-time visualization of this information through threat maps, charts, and alert logs. This allows analysts to quickly understand network conditions and respond effectively.

Table IV *presents system performance metrics.*

Metric	Value (%)	Description
Accuracy	98.2	Overall correctness of the model in classifying normal and attack traffic
Precision	97.6	Proportion of correctly identified attack instances among predicted attacks
Recall (Detection Rate)	96.8	Ability of the system to detect actual attack instances
F1-Score	97.2	Harmonic mean of precision and recall
False Positive Rate	2.1	Percentage of normal traffic incorrectly classified as attacks
Response Time	< 1 sec	Time taken to detect and respond to threats in real time

Relevance:

• Supports real-time monitoring

• Enables forensic analysis

• Improves decision-making

• Provides user-friendly interface

Performance Summary

The system achieves strong performance across standard evaluation metrics:

- Accuracy: ~98%
- Precision: ~97%
- Recall: ~96%
- F1-Score: ~97%
- False Positive Rate: ~2%
- Response Time: Less than 1 second

IV. IMPLEMENTATION AND RESULTS

This section explains how the network anomaly detection system was developed and evaluates its performance. It covers the implementation approach, tools used, experimental setup, and the results obtained from testing on both simulated and real network traffic. The system's effectiveness is measured using standard evaluation metrics to assess its capability for real-time threat detection and response.

A. Implementation Details

The system was developed using Python by integrating multiple libraries to support data processing, machine learning, and visualization tasks. It is designed to operate in real time, enabling continuous

monitoring and quick response to network threats. Network packets are captured using tools such as Scapy and PyShark. These packets are then grouped into flows based on attributes like source IP, destination IP, port, and protocol. From these flows, a set of statistical features is extracted to represent traffic behavior.

The detection module uses three models: Random Forest, Isolation Forest, and an Autoencoder. The Random Forest model is trained on labeled datasets, including CICIDS2017 and simulated traffic, to identify known attack patterns. Isolation Forest is used to detect anomalies in unlabeled data, while the Autoencoder learns normal traffic behavior and identifies deviations. A response module is integrated to automatically apply mitigation actions such as IP blocking and traffic rate limiting. All detected events are stored in CSV files and a SQLite database. For monitoring purposes, a Streamlit-based dashboard is used to display alerts, threat maps, and analytics in real time.

B. Tools and Technologies

The system is built using the following technologies:

- **Python** – Primary programming language
- **Scikit-learn** – Implementation of machine learning models
- **TensorFlow / Keras** – Deep learning model (Autoencoder)
- **Scapy / PyShark** – Network packet capture and analysis
- **Streamlit** – Development of real-time dashboard
- **SQLite** – Storage of alerts and logs

These tools enable efficient integration of different system components and support real-time processing.

C. Experimental Setup

The system was tested using a combination of simulated and real network traffic. The simulation module generated different types of attacks, including HTTP Flood, TCP SYN Flood, Port Scanning, SQL Injection, and UDP-based attacks. Experiments were conducted on a standard system configuration with moderate hardware resources. The models were evaluated using both training data and previously unseen traffic to measure their ability to detect known as well as unknown threats.

D. Performance Evaluation

System performance was evaluated using widely accepted metrics such as accuracy, precision, recall, F1-score, and false positive rate. The Random Forest model showed strong performance in classifying known attacks. Isolation Forest effectively identified anomalous patterns, while the Autoencoder was successful in detecting previously unseen or zero-day threats. Overall, the system achieved an accuracy of approximately **98%**, along with a low false positive rate. The response time remained under **one second**, demonstrating the system's capability for real-time detection and mitigation.

E. Results and Discussion

The evaluation results confirm that the system can effectively detect a wide range of network attacks. The combination of supervised, unsupervised, and deep learning models enhances detection performance while minimizing false positives. The SOC dashboard provides clear and real-time visualization of network activity, allowing users to quickly identify and respond to threats. The automated mitigation mechanism successfully blocks malicious sources, reducing the potential impact of attacks.

The system performs well for both known and unknown attack scenarios, making it suitable for real-world deployment. However, future improvements can include the use of more advanced deep learning models and larger datasets to further enhance accuracy and adaptability.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

In this work, we developed a Network Anomaly Detection and Real-Time SOC Monitoring platform that integrates machine learning with continuous network analysis and automated response mechanisms. The system overcomes the limitations of traditional intrusion detection approaches by combining supervised, unsupervised, and deep learning techniques to identify both known and previously unseen cyber threats.

Flow-based feature extraction is used to efficiently represent network behavior, while the combination of Random Forest, Isolation Forest, and Autoencoder models improves detection performance and minimizes false positives. The system demonstrates strong capability in detecting multiple types of attacks, including Distributed Denial of Service (DDoS), port scanning, and web-based threats.

The inclusion of a real-time SOC dashboard enables clear visualization of network activity, helping security analysts monitor and respond to incidents effectively. In addition, the automated mitigation module reduces response time by blocking malicious IP addresses and applying rate-limiting strategies. Experimental evaluation shows that the system achieves high accuracy, low latency, and reliable performance, making it suitable for both practical deployment and academic research.

B. Future Work

The system can be further improved by incorporating the following enhancements:

- Adoption of advanced deep learning models such as LSTM and Graph Neural Networks for detecting complex attack patterns
- Integration of real-time threat intelligence sources to improve detection accuracy and reduce false positives
- Extension to cloud and distributed environments for large- scale network monitoring
- Implementation of deep packet inspection techniques for analyzing encrypted traffic
- Integration with SIEM (Security Information and Event Management) platforms for enterprise-level deployment
- Enhancement of the SOC dashboard with more interactive and customizable visualization features
- Development of automated incident response workflows for faster and more efficient mitigation
- Expansion of training datasets using real-world traffic to improve model generalization
- Optimization of system performance for high-speed network environments
- Deployment as a scalable web-based solution for wider accessibility

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DIFFERENTIAL THERMAL ANALYSIS (DTA)

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ABSTRACT: Differential Thermal Analysis (DTA) is a widely used thermal analysis technique employed to study the thermal behavior of materials. In this method, the temperature difference between a sample and an inert reference material is measured as both are subjected to the same controlled heating or cooling program. Any thermal event occurring in the sample, such as phase transitions, decomposition, oxidation, crystallization, or melting, results in a temperature difference that is recorded as a DTA curve.

The technique provides valuable information about the thermal stability, phase transformations, and reaction temperatures of various materials including polymers, pharmaceuticals, minerals, and metals. DTA is particularly useful in determining characteristic temperatures such as melting point, crystallization temperature, and decomposition temperature. The resulting thermogram helps in identifying endothermic and exothermic processes, thereby aiding in material characterization and quality control. Due to its simplicity, sensitivity, and wide range of applications, Differential Thermal Analysis has become an important analytical tool in chemistry, materials science, and industrial research.

KEYWORDS: Differential Thermal Analysis (DTA), Thermal Analysis, Temperature Difference Measurement, Phase Transition, Thermal Decomposition, Endothermic Reaction, Exothermic Reaction, Thermograms, Sample–Reference Comparison, Heating Rate, Thermal Stability, Solid-State Reactions, Material Characterization, Phase Transformation, Ceramic and Polymer Analysis.

1. **INTRODUCTION:** Differential Thermal Analysis (DTA) is an important thermal analysis technique used to study the thermal behavior of materials as a function of temperature. In this method, the temperature difference between a sample and an inert reference material is measured while both are subjected to the same controlled heating or cooling program. Any thermal event occurring in the sample, such as melting, crystallization, phase transition, decomposition, or chemical reaction, results in a temperature difference that is recorded as a DTA curve.

The principle of DTA is based on the fact that when a material undergoes a physical or chemical change, it either absorbs heat (endothermic process) or releases heat (exothermic process). These heat changes cause a difference in temperature between the sample and the reference material. This temperature difference is plotted against temperature or time to produce a thermogram, which provides valuable information about the thermal properties and stability of the material.

Differential Thermal Analysis is widely used in various scientific fields such as chemistry, materials science, geology, pharmaceuticals, and polymer science. It is particularly useful for identifying phase transitions, determining reaction temperatures, and studying the thermal stability of substances. The technique also helps in characterizing materials, understanding reaction mechanisms, and evaluating purity.

Overall, DTA is a simple, reliable, and effective analytical method for investigating the thermal characteristics of different materials under controlled experimental conditions.

4. INSTRUMENTATION: The instrumentation of Differential Thermal Analysis (DTA) is designed to measure the temperature difference between a sample and a reference material while both are heated under identical conditions. The main components of a DTA instrument are described below.

Sample Holder

The sample holder contains two small crucibles or containers:

- Sample crucible – holds the material under investigation.
- Reference crucible – contains an inert material such as alumina (Al_2O_3) that does not undergo thermal changes.

Both crucibles are placed symmetrically to ensure uniform heating.

Furnace

A programmable **electric furnace** is used to heat the sample and reference simultaneously at a controlled rate (commonly 5–20 °C per minute).
The furnace provides a uniform temperature environment for accurate thermal comparison.

.**Thermocouples**

Two thermocouples are used in DTA instrumentation:

- One measures the temperature of the sample**.**
- The other measures the temperature of the reference material**.**

These thermocouples detect any temperature difference (ΔT) between the sample and the reference during heating.

Differential Temperature Measurement System

The temperature difference between the sample and reference is measured electronically.
When a thermal event occurs (such as melting, crystallization, or decomposition), a temperature difference is generated and detected by the system.

Temperature Controller

A programmed temperature controller regulates the heating rate of the furnace and ensures a constant heating schedule throughout the experiment.

Recording System / Data Acquisition

The differential temperature signal is sent to a recorder or computer-based data acquisition system.
The output is a DTA curve, which plots:

- Temperature (T) on the x-axis
- Temperature difference (ΔT) on the y-axis

Gas Flow System (Optional)

Some DTA instruments include a controlled gas atmosphere (such as nitrogen, air, or argon).
This helps prevent oxidation or allows reactions to occur under specific atmospheric conditions.

Summary of Main Components

8. Sample and reference crucibles
9. Furnace (controlled heating system)
10. Thermocouples
11. Differential temperature measuring unit
12. Temperature controller

13. Recording/data acquisition system
14. Gas flow or atmosphere control system

3. PRINCIPLE AND TECHNIQUE:

Principle

Differential Thermal Analysis (DTA) is a thermal analysis technique used to study the thermal behavior of materials. In this method, the temperature difference between a sample and an inert reference material is measured while both are subjected to the same heating or cooling program**.**

When the sample undergoes a physical or chemical change such as melting, crystallization, phase transition, or decomposition, it either absorbs heat (endothermic reaction) **or** releases heat (exothermic reaction). This causes a temperature difference (ΔT**)** between the sample and the reference material.

The measured temperature difference is recorded as a DTA curve**,** which shows peaks corresponding to thermal events.

Key idea:

- If the sample absorbs heat → endothermic peak appears.
- If the sample releases heat → exothermic peak appears.

Technique

The DTA technique involves the following steps:

Sample and Reference Preparation

- The test sample is placed in a small crucible.
- An inert reference material (such as **alumina, Al_2O_3**) is placed in another crucible.

Heating Program

- Both the sample and reference are heated simultaneously at a **constant heating rate** in a furnace.

Temperature Measurement

- Two **thermocouples** are used to measure the temperatures of the sample and the reference.

Detection of Temperature Difference

- The difference in temperature (ΔT) between the sample and reference is continuously monitored.

Recording the DTA Curve

- A plot of temperature difference (ΔT) versus temperature or time is recorded.
- Thermal events appear as peaks on the curve**.**

Interpretation of DTA Curve

- Endothermic peak → melting, dehydration, decomposition
- Exothermic peak → crystallization, oxidation, phase transformation

In summary:
Differential Thermal Analysis measures the temperature difference between a sample and an inert reference during controlled heating, allowing the detection of thermal transitions and reactions in materials.

4. Application: Differential Thermal Analysis (DTA) is a thermal analysis technique used to study physical and chemical changes in materials as a function of temperature. It has wide applications in chemistry, material science, geology, and pharmaceuticals.

i). Identification of Materials

DTA helps in the identification of substances by comparing their characteristic thermal curves with standard reference materials.

ii). Study of Phase Transitions

It is used to detect phase changes such as:

- Melting
- Crystallization
- Glass transition
- Polymorphic transformations

iii). Determination of Melting Point

DTA is commonly used to determine the melting temperature of pure substances and mixtures.

iv). Study of Chemical Reactions

It helps in analyzing endothermic and exothermic reactions, such as:

- Decomposition reactions
- Oxidation reactions
- Reduction reactions

v). Analysis of Minerals and Geological Samples

DTA is widely used in mineralogy and geology to identify clay minerals, ores, and other natural materials.

vi). Purity Determination

The technique can be used to check the purity of compounds by observing changes in the melting peak and thermal behavior.

vii). Study of Catalysts

DTA helps in examining catalytic reactions and catalyst stability at different temperatures.

viii). Polymer Analysis

It is used to study polymer properties such as curing, degradation, and thermal stability.

ix). Pharmaceutical Applications

DTA is applied to analyze:

- Drug–excipient compatibility
- Thermal stability of drugs
- Polymorphism in pharmaceutical compounds

x). Study of Glass and Ceramics

It is useful in investigating glass transition, crystallization, and sintering processes in ceramic materials.

✓ **In summary:** DTA is an important technique for studying thermal behavior, phase changes, reaction mechanisms, and material characterization**.**

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Rule and Behaviour-Based Intrusion and Ransomware Detection System for IoT and Cloud Environments

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Abstract—IoT and cloud computing keep growing, and so do cyber threats like network intrusions and ransomware. Instead of relying on heavy AI or machine learning models, this paper introduces a detection system that's both lightweight and efficient, built on rule-based and behaviour-based methods. The system has two main parts. First, the Intrusion Detection Module this one checks network traffic with signature rules and packet analysis. Then there's the Ransomware Detection Module, which spots nasty file behaviour through entropy analysis, hash checking, and even honeypot files to lure attackers. The whole setup delivers real-time detection without hogging resources, plus it's easy to understand. That makes it a solid fit for devices running on tight hardware and for cloud setups where scaling fast matters.

Keywords—Intrusion Detection System (IDS), IoT Security, Cloud Security, Ransomware Detection,

Rule-Based Detection, Behaviour-Based Detection, Honeypot Files.

I. INTRODUCTION

With so many IoT devices everywhere and everything moving to the cloud, our digital world has gotten wild—messy and more connected than ever. That's great for speed and convenience, but honestly, it's also opened the door to more headaches. Hackers have a ton of new ways to slip in. It's no wonder we keep hearing about network breaches and sneaky ransomware attacks popping up left and right.

To deal with these threats, a lot of security tools have started using Artificial Intelligence—mainly Machine Learning and Deep Learning.

Old-school, signature-based IDS work fast and nail known threats, but once attackers switch things up, these systems usually don't keep up. The newer AI-powered detection systems are better at spotting fresh or weird attacks by noticing odd behaviour. The catch? They burn through a lot of CPU and memory, so they're tough to run on smaller devices. Plus, good luck trying to explain how they come to their conclusions—the logic behind their choices is pretty much a black box. That lack of transparency, combined with how much power they need, just doesn't work for lightweight IoT devices.

This project aims for a more practical, middle-ground approach. Instead of leaning hard on AI, the idea is to use simple, easy-to-understand rules combined with targeted behavioural analysis. The end goal is a system that stays lightweight and transparent without sacrificing effectiveness for either IoT devices or the cloud. The push for this project comes from four big needs:

1) IoT devices run on limited power and processing. Throwing resource-hungry AI at them just isn't going to work.

2) In cybersecurity, people need to know why an alert was triggered. Clear, human-readable rules and behaviours make way more sense than vague probability scores.

3) Running detection right at the network edge—like on a gateway—lets you catch suspicious traffic and file changes without messing with every single device, and it speeds things up, too.

4) Small, tightly focused rulesets don't take up much memory and keep things running faster than bulky, complicated AI models. So, the main goal is simple: Build a lightweight system for spotting intrusions and ransomware using rule-based and behavioural techniques instead of AI—one that truly fits the needs of both IoT and cloud environments.

II. RELEATED WORK

Before coming up with a new system, it pays to look at how researchers are already tackling intrusion and ransomware detection. Most of the progress these days comes from machine learning, but there's still a solid amount of research into rule-based and behavioural detection—especially in situations where device resources are limited. Rahman and his team, in a 2025 survey, really push the need for lightweight, understandable IDS setups and better, more realistic IoT datasets. Sure, machine and deep learning methods hit high accuracy, but they also eat up a lot of computing power, and it's tough to figure out exactly how they make decisions. Other researchers go the behaviour-based route for ransomware—things like keeping an eye on I/O burst ratios and API calls. In lab tests, this kind of early detection actually works, catching threats quickly with almost no false alarms. Meanwhile, rule-based systems built for smart homes use less CPU and memory, keep networks running fast, and don't sacrifice detection. If you dig through the current literature, one thing is obvious: there's no single system that ties together the strong suits of both rule-based network intrusion detection and behaviour-based ransomware defence, without leaning on AI or machine learning. Right now, IDS tools don't block ransomware, and ransomware tools are either built around signatures or rely on AI. That's exactly the gap this project aims to fill.

III. PROPOSED METHODOLOGY

The proposed methodology is designed to overcome the limitations of existing systems by providing a transparent, lightweight, and dual layered detection system.

A. Existing System Limitations

Today's solutions are scattered all over the map. AI and machine learning power a lot of IDS tools, but they're resource hogs and you can't really tell how they come to their conclusions. Traditional antivirus tools just check for known signatures, making them pretty much useless against new, never-before-seen ransomware. Even strong IDS software like Snort or Suricata watch the network but stay blind to what's actually happening on the host's file system—so they miss ransomware activity there entirely.

B. Proposed System

We propose a Dual-Layered Detection Approach composed of two primary modules:

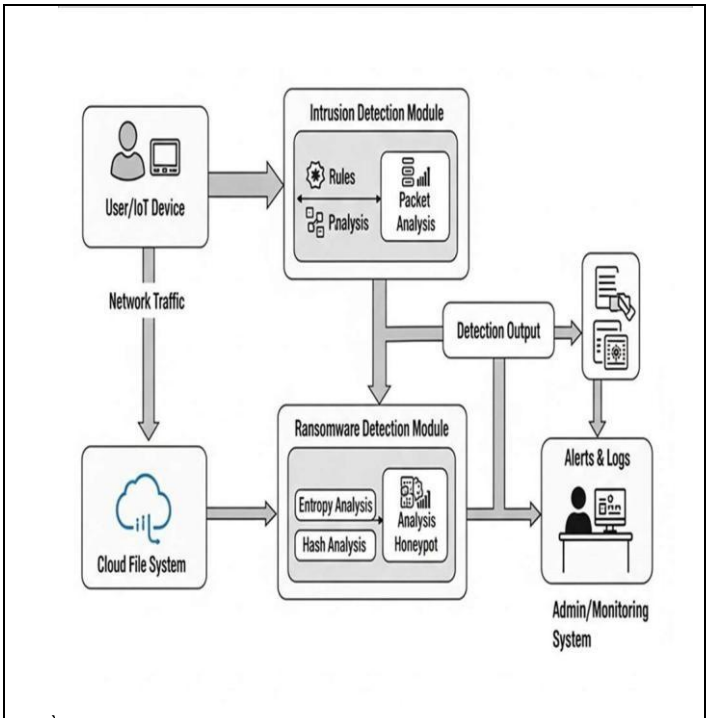

Figure 1: System Architecture

1) Intrusion Detection Module: This one handles network security. It looks for malicious patterns in network traffic using:

Snort/Suricata-style rules: These are plain, human-readable rules that spot known attack signatures.

- **Scapy-based analysis:** Goes deeper into packets, flagging suspicious activity like port scans, brute-force logins, and SQL injections.

2) Ransomware Detection Module: This piece is all about protecting your system from ransomware. It keeps an eye on your files, constantly scanning for anything suspicious—like files getting locked or renamed out of nowhere

A. Entropy Analysis: It checks how random your files look. If suddenly lots of files get way more random, chances are someone's encrypting them. That's a huge warning sign.

B. Cryptographic Hash Comparison: The system keeps a secure list of hashes—think SHA256—for your important files. If any of those files change out of the blue, the system catches it right away and raises a red flag.

C. Honeypot Files: It plants fake files in spots hackers love to target—like a "passwords.txt" decoy. If someone messes with these files, the system instantly sounds the alarm.

C. System Architecture

You can see how everything connects in Figure 1, but here's the gist:

1) Input Layer: It takes in all your network traffic—from users or IoT devices—and keeps an eye on everything happening in your local or cloud file system.

2) Monitoring Layer: This layer grabs network packets using Scapy and uses Python's Watchdog to keep track of every file change.

3) Detection Layer: All that info goes straight into the intrusion detection module, which checks rules and patterns, and the ransomware module, which runs the entropy analysis, hash checks, and honeypot file monitoring.

4) Alert & Reporting Layer: When something suspicious pops up, the system logs all the details and sends real-time alerts straight to the admins.

D. Modules Description

. Packet Capture & Analysis: Scapy scoops up raw network traffic and breaks it down on the fly. You get the key details—IP addresses, ports, protocols, and what's actually in the packets.

. Intrusion Detection: Compares each packet to the Snort/Suricata rules. Runs quick checks for things like many failed login attempts or port scans.

. Ransomware Detection: Uses Python tools to watch for trouble. It runs three checks at once—tracking file entropy, double-checking file hashes, and keeping an eye on honeypot files for suspicious access.

. Alert Generation & Reporting: Everything connects smoothly. When it spots a risk, it logs every detail, keeps track of the time, and shoots off instant alerts to the people who need to know.

IV. IMPLEMENTAION AND RESULTS

A. Implementation Details

We built everything in a virtual test environment using Python 3.The idea was pretty straightforward. One machine played the attacker, running Kali Linux. The other one was the target, running Ubuntu Server, almost like an IoT gateway or a cloud VM. We pulled all the main logic together in Python. Scapy handled network traffic capture, Watchdog tracked file changes, and Hashlib took care of the integrity checks. All the alerts go through a single system, which keeps tabs on both the network and the file system at once. So, we're catching signs of trouble from two angles at the same time.

B. Tools and Technologies

. Python 3: It's the core language running everything.

. Snort / Suricata: We loaded open-source rule sets to help with pattern matching.

. Scapy: Used for capturing the network packets.

. Watchdog: Handles file system event monitoring.

. Hashlib: Generates SHA256 hashes for integrity checks.

. Kali Linux: Source of test attacks, like Nmap, Hydra, and SQL Map.

. Wireshark: Used as a "ground truth" tool to double-check what our packet captures were seeing.

C. Results and Discussion

We put the system through a series of simulated attacks, and here's what happened:

. Port Scans: An Nmap TCP SYN scan didn't slip past us. Our Scapy-based sniffer caught the one-to-many connections coming from the attacker's IP and immediately flagged it.

. Brute-Force Attempts: When we hit the system with Hydra for SSH brute-forcing, the tool caught the rapid, repeated failed login attempts, pinpointing the attacker by IP.

. SQL Injection: We ran SQL Map attacks, and the system's packet inspection caught SQL injection payloads ("' OR '1'='1'", for example) right inside HTTP requests and sent out alerts. For ransomware detection, we ran a script that mimicked ransomware behaviour (reading, encrypting, and writing files):

. Entropy Analysis: As our mock ransomware encrypted text files, the Shannon entropy of those files shot up from 3.5 to 7.8. That was way over our set threshold, so the system flagged it as "Abnormal Encryption Activity."

. Honeypot Files: As soon as the script touched our decoy file, Watchdog triggered a high-priority "Honeypot Accessed" alert. This method responded the fastest, beating even entropy analysis in detection speed.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

We built a lightweight, transparent detection system that spots both intrusions and ransomware—specifically for IoT and cloud setups. The result? Real-time, clear alerts for a wide range of threats, without dragging down performance. It works well even in environments where resources are tight.

B. Future Work

There's still plenty of room to make this system even stronger:

1) Add a real-time, web-based monitoring dashboard (maybe with Flask).

2) Connect to live threat intelligence feeds so it can update its rules automatically.

3) Broaden its scope to catch things like data exfiltration and phishing.

4) Automate defenses like blocking an attacker's IP to turn it from just an IDS into a full-fledged Intrusion Prevention System (IPS).

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Empowering Indian SMEs to Embrace Sustainable Energy: A Conceptual Framework Using ReNew Power Partnerships

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Abstract:

The world – fast-paced with technical and technological advancements in every facet of development and growth, the terms 'sustainability' and 'sustainable practices' have to be remembered to achieve a balance in environmental, economic, social, and development initiatives. The world, with advancements, ever-changing, ever-dynamic, needs to stop in between to look into the effective and efficient use of resources and conservative practices to utilise the available resources by sustaining it for future generations.

The idea of sustainability began in the Industrial Revolution era, when production was massive with the introduction of new machines and improved factories. Though the industrial revolution brought equal wealth distribution, improved production methods, and employment opportunities, along with better living standards, the idea of exploiting natural resources kept taking a back seat. Many environmentalists and social clubs started noticing the gradual depletion of natural resources and the creeping emissions of greenhouse gases called voices against.

Since ancient times, sustainability has influenced all inventions. However, the 20th century saw a growing gap between technological advancement and the depletion of natural resources. In response, legal and environmental regulations were introduced, and strict control measures were implemented to address destructive practices.

This paper examines how ReNew, a 15-year-old Indian electric utility company, offers sustainable business solutions through decarbonisation techniques. ReNew aims to create grassroots impact with green hydrogen, data-driven solutions, energy storage, manufacturing, and carbon markets.

Keywords: Sustainability, Indian SMEs, sustainable business models, renewable energy, power purchase agreements

Introduction

With prospects of a rising global population, accelerating global development and associated increasing resource use and environmental impacts, it seems increasingly apparent that business as usual is not an option for a sustainable future. (N.M.P. Bocken*, S.W. Short, P. Rana, S. Evans). Sustainability concepts are newly introduced but dates back to the Burntland report and when the social and environmental initiatives took place. The Brundtland Report, published in 1987, helped to make the concept of sustainable development better known.

Considering the environmental and human aspects of business is crucial for companies while maintaining profits. Indian companies have taken several measures and have impacted the way people perceive business, leading many companies to pursue sustainability on their own. ReNew's sustainability approach is a combination of their purpose, strategy, and values, which is embodied in our ESG Policy to help us make valuable contributions to the environment and society. In this context, the integration of sustainability into core business strategies is no longer optional but essential for ensuring long-term value creation, responsible growth, and a balanced coexistence between economic success, environmental stewardship, and social well-being. The integration of advanced technologies such as data analytics, smart grids, and digital energy platforms has further strengthened the adoption of sustainable practices in modern businesses.

Indian SMEs:

The Micro, Small and Medium Enterprise (MSME) sector has emerged as a very important sector of the Indian economy, contributing significantly to the employment generation, innovation, exports, and inclusive growth of the economy. Micro, Small and Medium Enterprises (MSME) are the backbone of the socio-economic development of our country.(SME chamber of India).

With India's commitment to achieving net-zero emissions by 2070 and global climate targets becoming more ambitious, the role of Indian Micro, Small and Medium Enterprises (MSMEs) in driving environmental sustainability has become more crucial than ever. Indian MSMEs are taking steady, tangible steps to reduce greenhouse gas (GHG) emissions with initiatives such as shifting to clean energy, implementing energy-efficient manufacturing, promoting recycling and waste management, and embracing sustainable transportation solutions, among others. With grid tariffs climbing steadily, energy bills are eroding profitability. Many SME owners want to go solar, but are held back by capital costs and system maintenance concerns.

Power Purchase Agreements (PPAs)

A legally enforceable contract between an electricity buyer and seller is called a power purchase agreement (PPA).The contract terms can be modified in three ways: through contractual terms, negotiations between the parties, or in accordance with law.

PPA is essentially a tool that facilitates the sale and purchase of electricity.Thus, its existence is solely dependent upon the prospective customer having made a number of crucial decisions.All factors, including the need for power, the availability of power sources, the buyer's financial ability to obtain electricity, the desired power generating technology, and the power plant's location, must be taken into account.

A PPA is an agreement that lasts for a long period between an SME (the purchaser of electricity) and a solar developer (the supplier). Some of the benefits are,

- The developer is responsible for installing, owning, and maintaining the solar system.
- The SME is only responsible for paying for the electricity it consumes, often at an affordable rate compared to grid electricity.
- Contracts that span 10 to 25 years guarantee long-term price stability.
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ReNew Power:

ReNew, the leading provider of decarbonisation solutions in India, is committed to building a future without fossil fuels by developing innovative and sustainable solutions. ReNew celebrated its 15th year of operations in 2025, establishing a major milestone in its pursuit of sustainable energy leadership. ReNew is a company that has established itself as a leader in decarbonization solutions and is currently listed on Nasdaq (RNW, RNWWW).

Three layered ESG governance

ReNew's ESG governance framework is built on three layers to conduct business operations responsibly while staying true to the business's purpose.

● Environment goals - The main goal for 2025 is to establish foundational sustainability practices.The company's objective is to be validated as carbon neutral (Scope 1 and 2) on an annual basis and to create science-based goals for Scope 1, 2, and 3 emissions that have been validated by SBTi to achieve net-zero emissions.Furthermore, it has plans to procure 50% of its electricity from clean sources throughout all operations.By 2030, these endeavors will transform into more advanced and comprehensive sustainability objectives.

- The company aims to be environmentally conscious and achieve zero solid waste to landfill.Additionally, it aims to get 100% of its electricity from clean sources, indicating a complete switch to renewable energy across all operations.
- Social goals - By the year 2025, the company will be dedicated to building a workplace that is inclusive, safe, and aware.The plan is to pilot an all-female initiative across manufacturing sites, aim for zero lost-time injuries, and make sure all workers are aware of ESG.Furthermore, it aims to educate all of its security personnel on human rights and guarantee that there are no human rights violations within its operations. These initiatives will be expanded in scope and have a more significant impact on society and the workforce by 2030.Its commitment to ethics is extended by targeting the elimination of all human rights violations throughout the entire supply chain, which reflects a more inclusive and comprehensive approach to social responsibility.
- Governance goals - By 2025, the company aims to improve governance by incorporating a board diversity policy that includes 30% female representation, ensuring zero anti-competitive practices, linking ESG performance to executive compensation, and mitigating critical ESG risks within ERM frameworks.By 2030, its goal is to be recognized as a global leader by being placed among the top five energy utilities worldwide by ESG rating agencies like CDP, Sustainalytics, and Refinitiv, which shows strong governance and sustainability performance.

Corporate Power Purchase Agreements by ReNew

Commercial and industrial customers have the opportunity to procure renewable energy through long-term contracts through the Corporate Power Purchase Agreement (PPA) initiative by ReNew, which is a structured mechanism.Businesses don't need to invest in their own power generation infrastructure when they can buy clean electricity from ReNew directly at pre-agreed prices, ensuring cost stability and a steady supply of green energy.ReNew provides customized renewable energy solutions for various industries through its Green Solutions (RGS) platform.The list includes onsite solar installations, public wind and solar projects, hybrid energy systems, and flexible supply agreements, which are called virtual power purchase agreements (VPPAs).Organizations have the flexibility to pick solutions that fit their operational requirements, regulatory obligations, and sustainability goals, especially when it comes to reducing Scope 2 emissions.A key advantage of ReNew's PPA framework is its ability to support corporate decarbonisation while offering financial predictability. Businesses benefit from reduced exposure to fluctuating energy prices, compliance with renewable purchase obligations, and progress toward net-zero commitments. At the same time, the model facilitates large-scale adoption of renewable energy without requiring heavy capital investment. Digital platforms and automated energy management systems are increasingly being used to monitor and optimize power purchase agreements, enhancing transparency and efficiency.

Overall, ReNew's Corporate PPA offering is a critical enabler of the clean energy transition, bridging the gap between sustainability targets and practical implementation for enterprises.

Conclusion:

In conclusion, sustainability has changed from being an idea to something that every business needs to do in today's fast-changing world. This paper emphasizes the necessity of reconciling economic growth with environmental and social responsibility to guarantee sustainable development while preserving natural resources for future generations. The transition is even stronger because of the role of MSMEs in India, which are using cleaner technologies and more energy-efficient methods even though they face financial and infrastructure problems.

The ReNew study shows how large enterprises can successfully integrate sustainability into their business model through formalized ESG frameworks and innovative solutions such as Corporate Power Purchase Agreements (PPAs). ReNew is enabling the transition to a low-carbon economy by providing access to affordable renewable energy and supporting decarbonisation across industries. The integration of technological innovation with sustainability practices plays a crucial role in accelerating the transition toward a low-carbon and energy-efficient future.

Overall, it is suggested the need for a concerted effort from businesses, policy frameworks, and technological innovation to achieve sustainable development goals. ReNew, and others like it, prove that growth and environmental responsibility can be compatible, setting a precedent for a more sustainable and resilient tomorrow.

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AI-Assisted Smart Interview Preparation Platform

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ABSTRACT

This paper presents an AI-assisted smart interview preparation platform designed to simplify and enhance the technical interview preparation process through artificial intelligence. Traditional preparation methods lack personalization and real-time feedback, making role-specific learning difficult and inefficient. The proposed platform provides a structured, interactive, and adaptive learning environment tailored to different job roles and experience levels. The system securely authenticates users using JSON Web Tokens (JWT) and dynamically generates interview questions and answers using the Groq API, along with on-demand AI-powered explanations. Key features include an accordion-style interface for organized content browsing, pinned questions for quick revision, MongoDB-based session storage for progress tracking, and a responsive Tailwind CSS frontend built with React JS that ensures a smooth and engaging user experience. The platform supports multiple domains and interview formats including technical, HR, and behavioral interviews, positioning it as a comprehensive and scalable solution for modern interview preparation.

Keywords: *AI-Assisted Learning, Groq API, Interview Preparation, Personalized Education, JWT Authentication, MongoDB, React JS, Dynamic Question Generation, Adaptive Learning, MERN Stack*

I. INTRODUCTION

The technical interview process is one of the most critical gateways for professionals seeking employment in the technology sector. Despite its importance, a large proportion of candidates approach interviews inadequately prepared, often relying on static question banks, generic study guides, or informal peer advice that fails to address their specific job roles, experience levels, or skill gaps.

The rapid evolution of technology roles has further complicated interview preparation. A candidate applying for a machine learning engineering position requires a fundamentally different preparation strategy than one pursuing a frontend development or cloud architecture role. Yet most existing platforms treat all users identically, delivering the same curated question sets regardless of individual context.

Artificial Intelligence offers a transformative solution to these challenges. Large language models and generative AI APIs can dynamically produce relevant, role-specific interview questions and detailed explanations on demand, eliminating the need for manual content curation and enabling truly personalized preparation experiences. Combined with modern web technologies, these capabilities can be delivered through intuitive, accessible interfaces that support efficient study and revision.

This paper presents an AI-Assisted Smart Interview Preparation Platform that leverages the Groq API for dynamic content generation, JWT-based authentication for security, MongoDB for session persistence, and a React JS frontend with Tailwind CSS for a responsive user experience. The platform supports technical, HR, and behavioral interview preparation across multiple professional domains.

II. PROBLEM STATEMENT

Many existing interview preparation platforms rely on static and generic question sets that do not adapt to a user's job role or experience level, making focused and efficient preparation difficult. The core problems identified include:

- Static question banks that cannot adapt to individual job roles, skill levels, or emerging industry trends.
- Absence of intelligent content generation, resulting in outdated or irrelevant practice material.
- Lack of real-time AI-powered explanations for conceptual clarity and deeper understanding.
- Poor revision support with no mechanisms to prioritize or bookmark important questions.
- Inadequate session management, preventing users from tracking progress across study sessions.
- Limited interactivity that reduces user engagement and overall preparation effectiveness.
- No support for multiple interview formats such as technical, HR, and behavioral assessments.

These deficiencies collectively result in inefficient preparation experiences that fail to equip candidates with the confidence and competence required to succeed in modern technical interviews.

III. EXISTING SYSTEMS AND LIMITATIONS

Current interview preparation platforms fall into static content repositories, community-driven forums, and subscription-based practice platforms. Static repositories present pre-compiled question banks organized by topic or difficulty — easy to navigate but quickly outdated and unable to account for role-specific requirements.

Community-driven forums provide peer-sourced questions that reflect real experiences, but quality and relevance vary widely, moderation is inconsistent, and there is no mechanism for on-demand personalized explanations. Subscription-based platforms offer structured courses but involve significant financial costs that limit accessibility, and their content remains largely static and manually curated.

Across all categories, none offer dynamic AI-generated question sets, real-time explanations, intelligent session management, or adaptive personalization based on user profiles — capabilities that the proposed platform delivers.

IV. PROPOSED SYSTEM

A. AI-Driven Personalization

The platform introduces an intelligent interview preparation environment that dynamically adapts to individual users based on their job role, experience level, skill set, and learning progress. Upon authentication, users complete a profile setup that captures these parameters, which subsequently tailor all generated content. The system supports multiple professional domains and interview formats including technical, HR, and behavioral preparation.

B. Dynamic Content Generation

Rather than relying on pre-compiled static question banks, the platform generates dynamic, context-aware interview questions through the Groq API. Each question set is constructed based on the user's current profile, ensuring content is relevant, appropriately challenging, and aligned with contemporary industry expectations. On-demand AI-powered explanations are available for every question, enabling immediate conceptual deepening.

C. Interactive Learning and Revision Tools

The platform provides an accordion-style user interface that organizes questions and answers in a clean, collapsible format, reducing cognitive overload and enabling efficient navigation. Users can pin important or challenging questions to a personalized revision list accessible at any time. Revision tools including topic-wise practice, difficulty-level filtering, and mock interview simulation modes help users focus study efforts on areas requiring most attention.

D. Progress Tracking and Session Management

All user interactions, completed sessions, pinned questions, and performance metrics are persistently stored in MongoDB, enabling comprehensive progress tracking across multiple study sessions. JWT-based authentication provides secure, stateless session management that scales efficiently as the user base grows, protecting user data through industry-standard token-based authorization.

V. ALGORITHM

The AI-powered platform implements the following algorithmic pipeline:

Stage 1 — Secure Authentication: The user registers or logs in through a secure authentication module. JWT tokens are issued upon successful credential verification and included in all subsequent API requests.

Stage 2 — Profile-Based Personalization: Upon login, the system retrieves or prompts the user to complete a profile specifying job role, experience level, target companies, and skill domains. This profile forms the context for all subsequent Groq API content generation requests.

Stage 3 — Dynamic Question Generation: The user's profile parameters are formatted into a structured prompt and submitted to the Groq API, which returns a set of relevant, role-specific interview questions with detailed model answers generated in real time.

Stage 4 — On-Demand Explanation Generation: For any displayed question, the user can request a detailed AI-powered explanation. A targeted prompt is submitted to the Groq API and the returned explanation is rendered inline within the accordion interface.

Stage 5 — Question Pinning and Revision Management: Users can pin questions to a dedicated revision list stored in MongoDB. The pinning action is processed through the Node.js backend, persisting selections across sessions and devices.

Stage 6 — Session Storage and Progress Analytics: Upon session completion, all activity data is recorded in MongoDB. Aggregated analytics are presented to users in a progress dashboard, highlighting areas of strength and recommending targeted practice.

VI. TECHNOLOGIES USED

Frontend: React JS provides a component-driven reactive UI architecture; Tailwind CSS delivers utility-first, responsive styling. Backend: Node.js with Express.js manages RESTful API routing, JWT authentication, and Groq API integration. Database: MongoDB stores user profiles, session histories, pinned questions, and progress analytics with a flexible document schema that aligns naturally with the hierarchical data structure.

AI Integration: The Groq API serves as the generative AI engine for dynamic question generation and on-demand explanation delivery, providing low-latency response times critical for a real-time user experience. Security: JSON Web Tokens (JWT) provide stateless, cryptographically signed authentication for all protected API endpoints. Development Tools: Visual Studio Code (IDE), Thunder Client (API testing), Windows 10 64-bit (OS).

VII. EXPECTED OUTCOMES

Personalized Learning: Users receive dynamically generated interview questions and AI-powered explanations precisely tailored to their job role, skill set, and experience level, ensuring maximum relevance in every session.

Improved Interview Readiness: Consistent practice with role-specific AI-generated questions combined with on-demand conceptual explanations will significantly improve candidates' depth of understanding and confidence in actual technical interviews.

Efficient Revision: The pinned questions mechanism and accordion-style UI enable organized, prioritized revision lists that persist across sessions, improving long-term knowledge retention compared to unstructured study methods.

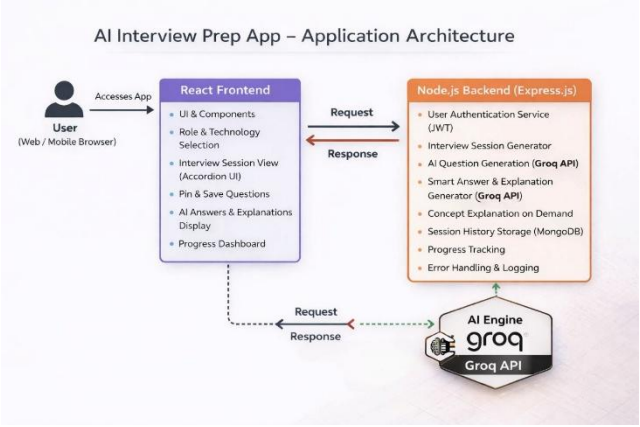
Comprehensive Progress Tracking: MongoDB-backed session storage enables a complete preparation history. Analytics identify weak areas and recommend targeted practice, improving overall study efficiency. The modular architecture allows straightforward extension to new roles, domains, or AI features without disrupting existing functionality.

VIII. SYSTEM DESIGN OVERVIEW

The platform's architecture follows a clear client-server separation with a dedicated AI integration layer. The React JS frontend communicates with the Node.js/Express.js backend through JWT-secured RESTful APIs. The backend coordinates between MongoDB for data persistence and the Groq API for AI content generation.

The accordion-style UI component structures the question-answer interface into collapsible panels, each displaying the question, a toggle to reveal the model answer, an explanation request button, and a pin control. Authentication follows a stateless flow: credential submission, JWT issuance, token storage at the client, and Bearer-token validation by Express.js middleware on every protected route.

Data models in MongoDB include User (profile, credentials, preferences), Session (timestamp, questions viewed, duration), Question (text, answer, domain, difficulty), and PinnedQuestion (user reference, question reference, timestamp). Indexed queries on user ID and session timestamp ensure efficient retrieval of progress analytics at scale.



IX. CONCLUSION

The AI-Assisted Smart Interview Preparation Platform addresses a significant and widely experienced challenge in professional development by delivering a personalized, intelligent, and interactive preparation environment powered by modern AI and web technologies. By replacing static question banks with dynamically generated, role-specific content from the Groq API, the platform ensures that every preparation session is relevant, current, and appropriately challenging.

The integration of JWT-based secure authentication, MongoDB-backed session persistence, and an intuitive accordion-style React JS interface creates a cohesive system supporting effective learning, efficient revision, and long-term progress tracking. The modular architecture ensures new domains, AI model upgrades, or additional features can be incorporated with minimal disruption.

Future enhancements will explore voice-based mock interview simulation to replicate real interview conditions, peer comparison analytics, multi-language support for non-English speaking candidates, and advanced learning analytics powered by machine learning models. The platform establishes a strong foundation for the next generation of AI-driven professional development tools.

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DEPRESSION DETECTION BASED ON TEXT AND FACIAL ANALYSIS FOR TEENAGERS

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ABSTRACT

Depression among teenagers has become a serious mental health issue due to academic pressure, social media influence, and lifestyle changes. Early detection plays a crucial role in preventing severe consequences. This paper presents a system for detecting depression using both textual data and facial expressions. Textual inputs such as chat messages are analyzed using Natural Language Processing (NLP) techniques, while facial expressions are analyzed using Convolutional Neural Networks (CNN).

The system evaluates emotional patterns and classifies depression levels into low, moderate, and high categories. Experimental results show improved accuracy compared to using a single method. The proposed system can assist in early identification and support mental health monitoring for teenagers.

Keywords: *Depression Detection, NLP, Facial Expression Recognition, CNN, Machine Learning, Teen Mental Health*

1. INTRODUCTION

Depression is a common mental health disorder affecting teenagers, impacting their emotions, behavior, and overall well-being. Increasing academic pressure, social media usage, and lifestyle changes have contributed to its rapid growth. Early detection is essential to prevent severe psychological effects, but traditional methods based on self-reporting and clinical evaluation are often delayed or inaccurate.

Recent advancements in Artificial Intelligence enable automated detection of emotional patterns. Text-based analysis using Natural Language Processing (NLP) helps identify sentiment from user-generated content, while facial expression analysis detects non-verbal cues such as sadness and stress. These techniques provide a more efficient and real-time approach to understanding mental health conditions.

The proposed system focuses on:

- Detecting depression levels in teenagers using textual data analysis.
- Identifying emotional states through facial expression recognition.
- Providing early-stage classification into low, moderate, and high depression levels.

By integrating Natural Language Processing (NLP) and deep learning techniques, the system aims to improve mental health awareness and support early intervention among teenagers.

2. LITERATURE SURVEY

Several research studies have explored depression detection using different techniques:

Text-based approaches use Natural Language Processing (NLP) to analyze user-generated data such as social media posts and messages. These methods are simple and effective but may fail to capture non-verbal emotional cues.

Facial expression-based approaches use computer vision and deep learning models such as Convolutional Neural Networks (CNN) to detect emotions from images. However, their performance depends on image quality and lighting conditions.

Recent studies indicate that combining textual and facial information can improve detection accuracy. However, many existing systems lack proper classification of depression severity levels and are not specifically designed for teenagers.

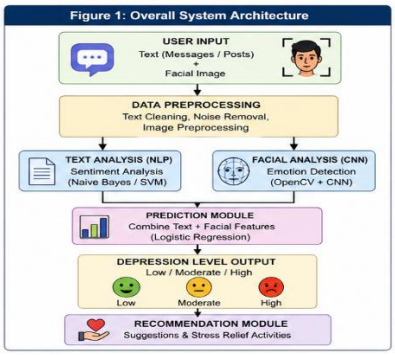
However, most existing systems:

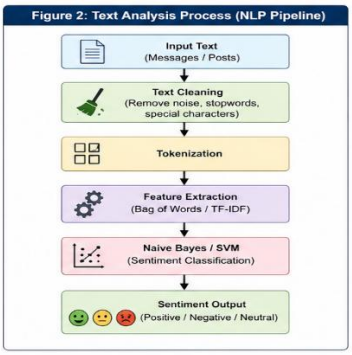
- Are complex and not easily understandable for general users
- Do not provide clear or timely indications of depression levels
- Lack user-friendly interfaces for interaction and monitoring
- Do not include proper support or alert mechanisms for early intervention

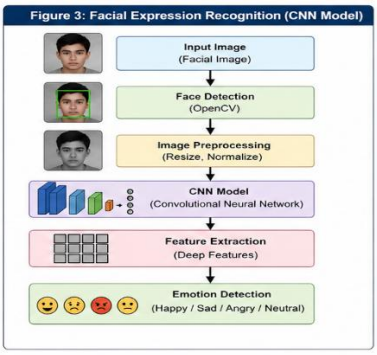
The proposed system overcomes these limitations by focusing on simplicity, usability, and real-time alerts.

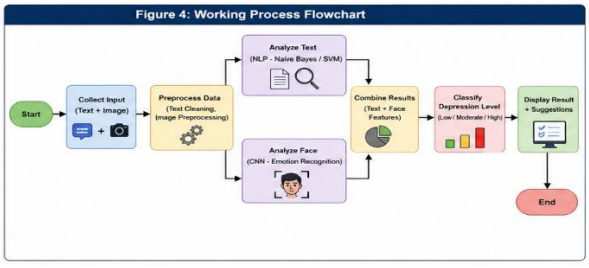
3. PROPOSED METHODOLOGY

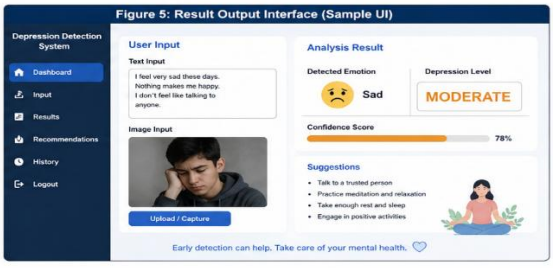
- The proposed system detects depression levels using both textual data and facial expressions. As shown in Fig. 1, user input includes text and facial images, which undergo preprocessing such as text cleaning and image normalization.
- Text analysis is performed using NLP techniques (Fig. 2), including tokenization, feature extraction (BoW, TF-IDF), and classification using Naive Bayes or SVM.
- Facial expression recognition is carried out using OpenCV and CNN models (Fig. 3) to detect emotions like happy, sad, angry, and neutral.
- The overall workflow (Fig. 4) combines outputs from both modules using Logistic Regression to classify depression levels as low, moderate, or high.
- The final results are displayed in a user interface (Fig. 5) along with emotion detection, depression level, and suitable recommendations.











3.1 System Architecture

The system consists of the following modules:

1. User Input Module

Accepts text input and facial images from users

2. Data Preprocessing Module

- Cleans text data
- Removes noise and unwanted characters
- Prepares image data

3. Text Analysis Module

- Uses NLP techniques
- Performs sentiment analysis

4. Facial Expression Module

- Uses OpenCV and CNN
- Detects facial emotions

5. Prediction Module

- Combines text and facial results
- Classifies depression level

6. Recommendation Module

- Provides suggestions
- Shows stress relief activities

3.2 Algorithms Used

Naive Bayes

- Used for text-based depression detection
- Based on probabilistic principles and Bayes' theorem
- Efficient for sentiment classification tasks

Convolutional Neural Network (CNN)

- Used for facial expression recognition
- Extracts features from facial images automatically
- Provides high accuracy in emotion detection

Logistic Regression

- Used for classification of depression levels
- Predicts probability based on input features
- Simple and effective for classification problems

Support Vector Machine (SVM)

- Used for emotion classification
- Separates data using a hyperplane
- Performs well with high-dimensional data

3.3 Working Process

1. Collects text and facial inputs
2. Preprocesses text and images
3. Extracts features using NLP and CNN
4. Analyzes data using ML models
5. Classifies depression level (Low/Moderate/High)

4. EXPERIMENT AND RESULTS

The proposed system was tested using different types of inputs including textual data (messages/posts) and facial images of teenagers.

Performance Metrics Used

- Accuracy
- Precision
- Recall
- F1 Score

Results

- High accuracy in detecting depression levels
- Fast response time
- Effective classification into Low, Moderate, and High levels

The system successfully provides:

- Real-time detection
- Clear output of depression levels
- Supportive suggestions for early awareness

5. CONCLUSION

This paper presents a **Depression Detection System for teenagers** that improves mental health monitoring using text and facial analysis techniques.

Key contributions:

- Real-time depression detection
- Simple and user-friendly result display
- Early identification of emotional patterns
- Efficient classification using machine learning and deep learning algorithms

The system is especially useful for teenagers and can assist in early detection of mental health issues, helping to promote awareness and timely intervention.

FUTURE WORK

- Integration with mobile applications
- Use of advanced deep learning models (LSTM, CNN improvements)
- Multi-language depression detection from text data
- Real-time monitoring and chatbot-based mental health support

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VISION-BASED TELEREHABILITATION ECOSYSTEM

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ABSTRACT

Rehabilitation therapy requires accurate exercise execution, continuous monitoring, and consistent feedback, which are often difficult to achieve outside clinical settings. This project proposes a vision based hand telerehabilitation ecosystem that uses computer vision to support remote hand recovery and improve accessibility to therapy.

The system performs real-time motion tracking to monitor patient movements, automatically count repetitions, and measure the time taken to complete each exercise. It provides immediate feedback to both patients and healthcare professionals, ensuring exercises are performed correctly and progress is clearly visible. A unified dashboard displays repetition count, performance accuracy, and time-based metrics to support better evaluation and guidance.

To enhance engagement and improve fine motor skills, the system also integrates interactive finger-based rehabilitation games. These games are designed to support hand movement, coordination, and flexibility, while being monitored through vision-based analysis. By combining automated tracking, feedback, and gamified rehabilitation, the system aims to make recovery more effective, measurable, and engaging.

Keywords: Hand moment tracking, computer vision, remote healthcare, hand rehabilitation monitoring, motion tracking, repetition counting,digital therapy, healthcare AI.

1. INTRODUCTION

Hand rehabilitation therapy often requires continuous supervision, precise exercise execution, and consistent monitoring, which can be challenging for patients due to limited access to healthcare facilities, cost constraints, and geographical barriers. Patients performing exercises at home may struggle with incorrect posture, lack of guidance, and reduced motivation, leading to slower or ineffective recovery.

Traditional rehabilitation methods rely heavily on in-person sessions and manual observation, making them less scalable and difficult to maintain over long periods. Existing remote solutions often lack real-time tracking, accurate performance evaluation, and engaging mechanisms to keep patients consistent. There is a clear need for an intelligent, accessible, and interactive system that can support patients remotely while ensuring proper rehabilitation practices.

The proposed system focuses on:

- Tracking patient movements in real-time using computer vision
- Counting repetitions and measuring time taken for each exercise

• Displaying performance metrics through a patient dashboard
• Enhancing engagement through interactive finger-based rehabilitation games

By combining vision-based analysis with automated tracking and gamified interaction, the system aims to improve rehabilitation accuracy, increase patient adherence, and provide a scalable solution for effective remote recovery.

2. LITERATURE SURVEY

Several research works have been carried out in the field of hand telerehabilitation using computer vision and intelligent healthcare systems. Recent studies propose vision-based frameworks for monitoring patient exercises using techniques such as human pose estimation and motion tracking. Algorithms and models based on deep learning and image processing are widely used to analyze body posture and detect movement patterns during rehabilitation sessions.

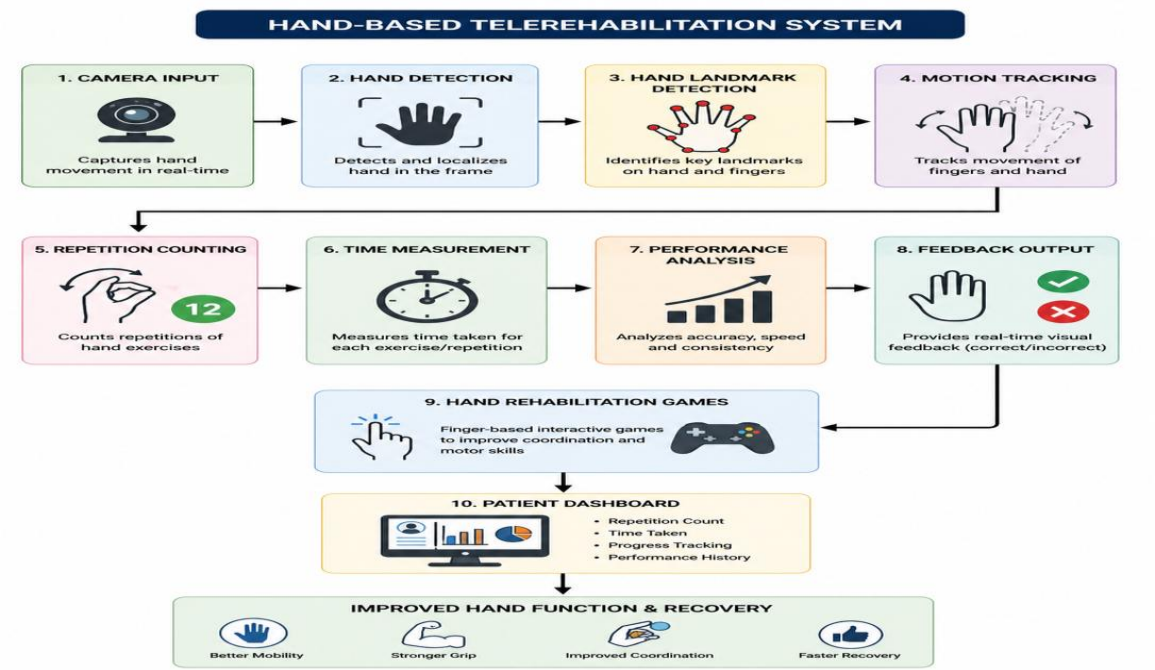
Other works focus on automated performance evaluation by measuring parameters like joint angles, movement accuracy, and exercise completion. Some research also explores gamification approaches, where interactive systems and virtual environments are used to improve patient engagement and motivation, especially for hand and finger rehabilitation. These systems aim to make therapy more interactive while maintaining clinical relevance.

Computer vision-based rehabilitation solutions have shown promising results in enabling remote monitoring and improving exercise adherence. However, most existing systems:
• Lack accurate real-time repetition counting and time-based performance tracking
• Provide limited feedback on exercise quality and consistency
• Do not effectively integrate engaging elements like finger-based rehabilitation games
• Are not designed as scalable and user-friendly systems for continuous home-based use

3. PROPOSED METHODOLOGY

• Real-time vision-based tracking to monitor hand movements, count repetitions, and measure time taken for each exercise

• Integration of finger-based rehabilitation games to improve engagement, coordination, and motor skill recovery



3.1 System Architecture

The system consists of the following modules:

1.Patient Input
- Camera / Video Input
- Hand Movement Capture

2.Data Collection
- Live Video Stream
- Frame Capture

3.Data Preprocessing
- Frame Extraction
- Noise Removal
- Normalization

4.Feature Extraction
- Hand Landmark Detection
- Finger Tracking
- Motion Features

5.Movement Analysis
- Repetition Counting
- Time Measurement
- Movement Accuracy

6.Dashboard & Visualization
- Repetition Count
- Time Taken
- Progress Tracking

7.Rehabilitation Games
• Finger-based Games
• Coordination Improvement
• Motor Skill Enhancement

3.2 Algorithms Used
MediaPipe Hand Landmark Detection
• Detects 21 key points on the hand in real time
• Provides precise finger and joint positions
• Forms the base for all movement analysis

Hand Tracking Algorithm
• Tracks hand movement across consecutive frames
• Maintains continuity of motion
• Helps analyze exercise patterns

Finger State Detection
• Identifies whether fingers are open or closed
• Uses landmark positions for classification
• Helps in gesture and exercise recognition

Repetition Counting Algorithm
• Counts repetitions based on movement cycles
• Uses positional or angle changes
• Ensures accurate exercise count

Time Measurement Algorithm
• Measures time taken per repetition/session
• Tracks exercise duration
• Helps evaluate speed and consistency

Gesture-Based Game Control
• Maps finger gestures to game actions
• Enables interactive rehabilitation games
• Improves engagement and motor skills

3.3 Working Process

1. Patient performs hand exercises in front of the camera
2. System captures real-time video of hand movements
3. Hand landmarks are detected using a vision-based model
4. Movement data is processed and analyzed
5. System counts repetitions and measures time taken
6. Movement accuracy is evaluated based on predefined patterns
7. Results are displayed on the patient dashboard with progress tracking
8. Finger-based rehabilitation games are used to improve coordination and engagement

4. EXPERIMENT AND RESULTS

The proposed system was tested using real-time rexercise repetation count of hand rehabilitation exercises. Different hand movements and finger exercises were performed to evaluate the system's ability to track motion, count repetitions, and measure time accurately.

Performance Metrics Used

- Repetition counting accuracy
- Time measurement accuracy
- Movement detection consistency
- System response time

Results

- Accurate detection of hand movements using vision-based tracking
- Reliable repetition counting across multiple exercise sessions
- Consistent time measurement for each exercise
- Smooth real-time performance without noticeable delay
- Improved user engagement through finger-based rehabilitation games

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The system successfully provides:

- Real-time hand movement tracking using vision-based analysis
- Accurate repetition counting and time measurement for each exercise
- Clear visualization of performance metrics through a patient dashboard
- Interactive finger-based rehabilitation games to improve engagement and motor skills

6. CONCLUSION

This project presents a Vision-Based Telerehabilitation Ecosystem designed to support remote hand rehabilitation using computer vision techniques.

Key contributions:

- Real-time hand movement tracking using vision-based analysis
- Accurate repetition counting and time measurement for exercises
- Patient dashboard for clear visualization of performance metrics
- Integration of finger-based rehabilitation games to improve engagement and motor skills

The system improves rehabilitation by making therapy more accessible, consistent, and interactive, providing an effective and scalable solution for home-based recovery.

FUTURE WORK

1.Integration with mobile applications for easier access and portability
2. Implementation of advanced deep learning models for improved hand tracking accuracy
3. Support for additional rehabilitation exercises beyond hand movements
4.Inclusion of personalized therapy plans based on user performance
5.Enhanced gamification with more interactive and adaptive rehabilitation games
6.Multi-user support for therapists to monitor multiple patients
7.Integration with wearable sensors for more precise movement analysis

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Citizen Participation in Smart Cities through E-Governance Platforms: A Study of Hyderabad

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Abstract:

The evolution of digital technology has greatly impacted urban governance in the sense that it led to the creation of smart cities, characterized by efficiency, transparency, and citizen-oriented services. E-governance systems have played an important role in ensuring that the interaction between government agencies and citizens takes place because they ensure access to public services and facilitate citizen involvement. Citizen participation is, therefore, one of the determinants of the success of smart city initiatives. This research seeks to analyse the degree of participation of citizens in the smart city initiative in Hyderabad through the use of e-governance digital systems and assess their impact on increasing citizen involvement. The research will focus on the awareness, usage, and satisfaction of citizens when using digital systems for governance. Moreover, it will also explore the various challenges faced by citizens in the process of participating in smart city projects. Both primary and secondary sources will be used for gathering the information required for the research. Primary data will be collected through the use of structured questionnaires distributed to the citizens of Hyderabad. Secondary data will be obtained from government publications, previous studies, and other relevant literatures on smart cities. Data analysis is done using statistical methods to show the relationship among factors affecting citizens' participation. The outcome of this research will reveal the extent to which citizens can use e-governance platforms to improve their experiences in service provision, transparency, and participation. The research also provides recommendations on ways that can be used to overcome some of the challenges that inhibit the use of e-governance for participation. This research will therefore contribute immensely to the literature in this area of e-governance in Hyderabad.

KeyWords: E-Governance, Smart Cities, Citizen Participation, Digital Platforms, Digital Transformation, Civic Engagement, Urban Governance, Public Service Delivery

Introduction:

In the contemporary era of rapid digital transformation and urbanization, cities across the globe are increasingly adopting technology-driven governance models to enhance efficiency, transparency, and service delivery. The concept of e-governance has emerged as a pivotal mechanism through which governments utilize digital platforms, information and communication technologies (ICT), and data-driven systems to interact with citizens and deliver public services. Simultaneously, the notion of smart cities has gained prominence as an integrated approach to urban development that leverages technology to address complex challenges such as population growth, resource management, infrastructure demands, and environmental sustainability. In this context, e-governance forms the backbone of smart city initiatives by enabling seamless communication between government institutions and citizens, thereby fostering a more responsive and accountable governance system.

A critical dimension of smart city development is **citizen participation**, which is widely recognized as essential for ensuring inclusive, democratic, and effective governance. Digital platforms such as mobile applications, online grievance redressal systems, and citizen engagement portals have been introduced to

facilitate public involvement in decision-making processes, service feedback, and urban planning. These platforms are expected to transform citizens from passive recipients of services into active stakeholders in governance. However, despite the widespread adoption of e-governance systems, concerns remain regarding the extent to which these digital tools genuinely enable meaningful participation or merely serve as channels for basic service utilization.

In developing countries like India, the implementation of the Smart Cities Mission has accelerated the integration of e-governance platforms into urban governance frameworks. Cities such as Hyderabad, known for their technological advancement and digital infrastructure, provide a significant context for examining the effectiveness of such initiatives. While these platforms have improved access to services and information, several challenges persist, including the digital divide, lack of awareness, usability issues, and trust deficits among citizens. These factors often limit the potential of digital governance systems to achieve true participatory outcomes.

Moreover, existing studies suggest that the success of e-governance in smart cities is not solely dependent on technological infrastructure but also on socio-economic conditions, institutional capacity, and citizen readiness. The gap between the availability of digital platforms and their effective utilization highlights the need for a deeper evaluation of citizen engagement mechanisms. Understanding whether citizens actively participate in governance or merely interact with services is crucial for assessing the effectiveness of smart city initiatives.

Against this backdrop, the present study focuses on Hyderabad to examine the level of awareness and usage of e-governance platforms, assess the extent of citizen participation through digital systems, and identify the key barriers that hinder effective engagement. By analyzing these dimensions, the study aims to provide insights into the role of digital platforms in shaping participatory governance and to suggest pathways for creating more inclusive, citizen-centric smart city ecosystems. This research contributes to the growing body of literature on e-governance and smart cities by emphasizing the importance of bridging the gap between technological advancement and meaningful citizen participation.

Literature Review

1. David Bastos, Antonio Fernández-Caballero, António Pereira, and Nelson Pacheco Rocha (2022), in their study titled "Smart City Applications to Promote Citizen Participation in City Management and Governance: A Systematic Review", examine the role of smart city technologies in enhancing citizen participation in urban governance. The primary objective of the study is to analyze existing research on applications that enable citizens to actively contribute to city management and decision-making processes. The research adopts a systematic review methodology, where 76 relevant studies were selected and analyzed based on predefined inclusion and exclusion criteria. The findings reveal that most smart city applications focus on enabling citizens to report urban issues, monitor environmental conditions, and share opinions through digital platforms such as crowdsourcing and social media. However, only a limited number of applications support active citizen involvement in decision-making processes. The study also identifies key challenges, including issues related to data quality, privacy, security, and lack of effective strategies to motivate citizen participation. Overall, the research highlights the growing importance of citizen-centric digital platforms while emphasizing the need for more inclusive and participatory governance models in smart cities.

2. Seunghwan Myeong and Syed Asad Abbas Bokhari (2023), in their study titled "Building Participative E-Governance in Smart Cities: Moderating Role of Institutional and Technological Innovation", examine the relationship between e-governance and stakeholders' satisfaction in smart cities. The primary objective of the study is to analyze how institutional and technological innovation influence this relationship. The research adopts a quantitative approach using primary data collected through structured questionnaires from 589 respondents across the Republic of

Korea and Pakistan. The data were analyzed using multiple regression techniques to test the proposed hypotheses. The findings reveal that e-governance significantly enhances stakeholders' satisfaction by improving service delivery, communication, and citizen engagement. Furthermore, the study highlights that both institutional innovation and technological innovation positively influence stakeholders' satisfaction and act as moderating factors that strengthen the relationship between e-governance and satisfaction. The research concludes that effective implementation of innovative governance structures and advanced technologies is essential for achieving successful and participatory smart city governance.

3. Waghmare (2024), in her study titled "Democratic Participation and Smart City Citizenship in Emerging Economies – Case of Smart Cities in India", examines the extent and nature of citizen participation in smart city governance in India. The primary objective of the study is to evaluate whether democratic participation mechanisms in smart cities are effective and inclusive. The research adopts a mixed-method approach, combining quantitative assessment of 21 smart cities with qualitative case studies of Kochi and Nagpur. The findings reveal that citizen participation in most Indian smart cities remains largely "tokenistic", with limited involvement of stakeholders in actual decision-making processes. The study identifies significant barriers such as bureaucratic control, elite dominance, digital divide, and lack of institutional capacity, which restrict meaningful participation. While cities like Kochi demonstrate relatively higher levels of citizen engagement through participatory budgeting and ward committees, others like Nagpur exhibit low levels of participation characterized by non-participation and limited citizen power. The study concludes that for smart cities to become inclusive and sustainable, governance must shift towards a more democratic, accountable, and collaborative model that empowers citizens beyond mere consultation.

4. Das (2024), in his study titled "Exploring an ICT-Enabled Participative Smart City Governance System: An Indian Context", examines the role of Information and Communication Technology (ICT) in enhancing participatory governance in Indian smart cities. The study aims to analyse the effectiveness of existing governance structures and assess how ICT can enable inclusive and responsive decision-making. Adopting a mixed-method approach, the research combines secondary data analysis with a Delphi survey of 44 experts across governance, planning, and policy domains. The findings reveal that current smart city governance in India is largely centralised, with Special Purpose Vehicles (SPVs) overshadowing Urban Local Bodies (ULBs), thereby weakening democratic accountability and citizen participation. Furthermore, ICT is primarily utilised for routine administrative functions and service delivery, while its potential for enabling stakeholder engagement and participatory decision-making remains underutilised. The study also highlights key challenges such as the digital divide, limited institutional capacity, and fragmented governance structures. To address these issues, the paper proposes an ICT-enabled participatory governance framework grounded in cultural theory and pluralist democracy, emphasising collaboration among diverse stakeholders. The study concludes that effective integration of ICT with inclusive governance mechanisms is essential for achieving responsive, transparent, and citizen-centric smart city development.

5. Praharaj, Han, and Hawken (2017), in their study titled "Innovative Civic Engagement and Digital Urban Infrastructure: Lessons from 100 Smart Cities Mission in India", examine the effectiveness of ICT-based citizen engagement initiatives in India's Smart Cities Mission. The study aims to analyse the relationship between digital infrastructure, socio-economic factors, and the intensity of citizen participation through online platforms such as MyGov.in. The research adopts a mixed-method approach, combining secondary data analysis of 100 smart cities with correlation analysis and semi-structured interviews. The findings reveal significant variations in citizen participation across cities, with many urban areas demonstrating low levels of engagement despite the availability of digital platforms. Notably, the study highlights that increased access to digital infrastructure, such as internet and mobile connectivity, does not necessarily lead to higher levels of citizen participation. Furthermore, the centralised nature of the MyGov platform limits local-level interaction, resulting in passive and less effective engagement. The study concludes that

successful e-participation requires not only technological infrastructure but also strong local governance, citizen awareness, and context-specific strategies to foster meaningful civic engagement.

6. Sharma and Agawane (2024), in their study titled "Smart Cities Mission", examine the implementation, governance, and impact of India's Smart Cities Mission launched in 2015. The primary objective of the study is to analyse how the mission integrates technology, governance structures, and citizen engagement to enhance urban development and quality of life. The research adopts a descriptive and analytical approach, utilizing both primary and secondary data sources to explore various dimensions of the mission, including funding models, technological integration, and urban infrastructure development. The findings highlight that citizen participation plays a crucial role in aligning urban development initiatives with public needs, while technologies such as IoT, artificial intelligence, and big data analytics significantly improve service delivery and resource management. However, the study also identifies several challenges, including financial constraints, bureaucratic delays, digital divide, low public awareness, and data privacy concerns. The research concludes that while the Smart Cities Mission has contributed to improved urban infrastructure and governance, its success largely depends on effective citizen engagement, technological integration, and inclusive policy implementation.

7. Anand, Sreevatsan, and Taraporevala (2018), in their study titled "An Overview of the Smart Cities Mission in India", critically examine the governance, financing, and citizen participation mechanisms within India's Smart Cities Mission. The primary objective of the study is to understand the structural and operational dynamics of the mission using empirical data derived from government documents across 99 smart cities. The research adopts a data-driven analytical approach, evaluating project details, governance structures, and participation modalities. The findings reveal that despite the emphasis on participatory governance, citizen engagement in the Smart Cities Mission remains limited and inadequately documented, with many cities failing to provide clear evidence of meaningful public involvement. The study also highlights that the creation of Special Purpose Vehicles (SPVs) has led to the recentralization of power, reducing the role of local urban bodies and weakening democratic processes. Furthermore, the focus on area-based development has contributed to urban inequality, as a large portion of city resources is concentrated in limited areas. The research concludes that the Smart Cities Mission prioritizes infrastructure and economic growth over inclusive governance, thereby raising concerns about the effectiveness of citizen participation in smart city development.

8. Basu (2025), in his study titled "Engage Citizens to Smarten City Governance", examines the role of citizen participation in enhancing smart city governance under India's Smart Cities Mission. The primary objective of the study is to identify the challenges and enabling factors influencing public participation in urban governance. The research adopts a qualitative approach based on literature review, supported by field-level surveys, consultations, and a case study of the Pune Smart City project. The findings reveal that although the Smart Cities Mission emphasizes the use of e-governance and ICT tools to promote citizen engagement, participation often remains superficial and ceremonial in nature. The study identifies major barriers such as digital divide, digital illiteracy, bureaucratic control, political intervention, and top-down governance structures, which limit meaningful citizen involvement. Furthermore, the case study highlights that lack of awareness, ineffective communication strategies, and exclusion of marginalized groups hinder successful implementation of participatory initiatives. However, the research also notes that cities with visionary leadership and inclusive governance practices demonstrate relatively higher levels of citizen engagement. The study concludes that effective citizen participation requires a shift towards more inclusive, transparent, and interactive governance frameworks that actively involve citizens throughout the decision-making process.

9. Kshirsagar and Joshi (2025), in their study titled "Transforming Urban Development in India: The Role of IoT in Smart Cities", examine the role of Internet of Things (IoT) technologies in enhancing urban governance and service delivery within India's smart cities framework. The primary objective of the study is to analyse the applications, benefits, and challenges of IoT-enabled systems in urban development. The research adopts a qualitative approach based on literature review and case studies of selected Indian cities, including Pune, Indore, Hyderabad, and Chennai. The findings reveal that IoT technologies facilitate real-time data collection, monitoring, and decision-making, thereby improving efficiency in sectors such as transportation, waste management, water distribution, environmental monitoring, and public safety. The study also highlights that IoT-enabled platforms contribute to the development of smart governance systems and support citizen-centric service delivery. However, several challenges, including data privacy concerns, infrastructure limitations, financial constraints, and low levels of digital literacy, hinder effective implementation. The research concludes that while IoT has significant potential to transform urban governance and enhance citizen participation, its success depends on inclusive implementation, strong policy frameworks, and improved digital awareness among citizens.

10. Sadoway and Shekhar, in their study titled "(Re)Prioritizing Citizens in Smart Cities Governance: Examples of Smart Citizenship from Urban India", critically examine the dominant technology-driven approach to smart city development and emphasize the need to reposition citizens at the center of urban governance. The primary objective of the study is to distinguish between commercially driven smart city models and community-oriented "smart citizenship" approaches. The research adopts a conceptual and case study-based approach, drawing on the example of Transparent Chennai to illustrate how citizen-led initiatives can enhance governance and accountability. The findings reveal that conventional smart city frameworks often prioritize technological solutions and corporate interests, resulting in limited citizen participation, increased inequality, and exclusion of marginalized groups. In contrast, the concept of smart citizenship emphasizes the importance of local knowledge, community engagement, and participatory decision-making processes supported by ICT tools. The study concludes that effective smart city governance requires a shift from technology-centric models to citizen-centric approaches, where digital platforms serve as enablers of inclusive and democratic participation rather than mere tools for data collection and service delivery.

Research gap

Literature on smart cities and e-governance largely concentrates on technology and policy, leaving aside any discussion about citizen participation that remains passive and tokenistic. Many sources used in the research are secondary and theoretical, and there is no sufficient data from empirical studies based on primary data sources to analyze citizen engagement in reality. Issues of awareness, use, satisfaction, and trust in e-governance systems have not been studied sufficiently. Problems related to the digital divide, low levels of digital literacy, and socioeconomic disparities have been discussed, but their implications for citizen participation have not been investigated properly. Moreover, centralized models of governance hinder effective citizen participation. In addition, city-specific research has not been conducted widely, especially regarding Hyderabad, even though it is a leading smart and IT-enabled city.

Objectives of the study:

1. To examine the level of awareness and actual usage of e-governance platforms among citizens in Hyderabad.
2. To assess the extent of citizen participation in smart city governance through digital platforms.
3. To identify key challenges and barriers that limit effective citizen engagement in e-governance systems.

Scope of the Study:

The current research study concentrates on the analysis of the citizen engagement process in smart city management using e-governance portals in Hyderabad. This study will include important aspects like

citizen awareness, usage patterns, degree of engagement, satisfaction, and difficulties encountered during their engagement with e-governance processes. The scope of this research study includes only urban populations having prior experience with e-governance portals.

Limitations of the Study

There are some limitations that could impact the generalizability of the results obtained in the current study. First of all, the study has a narrow geographical focus – the City of Hyderabad. In addition, the study is based on a limited number of respondents, and the sample does not cover all types of population groups. Data used for the study is subjective because it is based on the perceptions of the respondents regarding the e-governance system. Moreover, there could be some limitations regarding access to reliable secondary data as well as the limited period during which data is collected. Finally, there could be differences among participants in their technological skills and access to information technology.

Hypothesis:

Hypothesis Testing

For the two-hypothesis framed, CHI SQUARE is performed. CHI SQUARE is used to determine if a difference between observed data and expected data

Objective 1:

To examine the level of awareness and actual usage of e-governance platforms among citizens in Hyderabad.

Hypothesis

- **H_{01} (Null Hypothesis):** There is **no significant association** between citizens' awareness and their usage of e-governance platforms.
- **H_{11} (Alternative Hypothesis):** There is a **significant association** between citizens' awareness and their usage of e-governance platforms.

Observed Frequency Table

Awarness/Usage	Use	Do not Use	Total
Aware	20	10	30
Not aware	5	15	20
total	25	25	50

Expected Frequency Table

Formula: E = (Row Total × Column Total) / Grand Total

Awarness/Usage	Use	Do not Use
Aware	30x25/50=15	30x25/50=15
Not aware	20x25/50=10	20x25/50=10

Chi-Square Calculation

Category	**O**	**E**	**$(O-E)^2/E$**
Aware-use	20	15	1.67
Aware=not use	10	15	1.67
Not Aware-use	5	10	2.5
Not Aware-not use	15	10	2.5

Calculated χ^2 value = 8.34
Degrees of Freedom
Degree of Freedom = (no. of rows − 1) (no. of columns− 1)
(2 − 1) (2 − 1)
= **1**
Level of significance = 5%
Critical value = 3.84
Chi-square value=8.34
8.34 > 3.84 → Reject H_0
Conclusion: Awareness significantly affects usage.

Objective 2:

To assess the extent of citizen participation in smart city governance through digital platforms.

Hypothesis

- **H_{02} (Null Hypothesis):** There is **no significant relationship** between the use of e-governance platforms and citizen participation in smart city governance.
- **H_{12} (Alternative Hypothesis):** There is a **significant relationship** between the use of e-governance platforms and citizen participation in smart city governance.

Observed Frequency Table

Users / Participants	Participate	Do not participate	Total
Users	18	7	25
Not Users	6	19	25
Total	24	26	50

Expected Frequency Table

Formula: E = (Row Total × Column Total) / Grand Total

Users / Participants	Participate	Do not participate
Users	12	13
Not Users	12	13

Chi-Square Calculation

Category	**O**	**E**	**$(O-E)^2/E$**
Users-Participate	8	12	3.00
Users- Do not participate	7	13	2.77
Not Users - Participate	6	12	3.00
Not Users - Do not participate	19	13	2.77

Calculated χ^2 value = 11.54
Degrees of Freedom
Degree of Freedom = (no. of rows − 1) (no. of columns− 1)
(2 − 1) (2 − 1)= **1**
Level of significance = 5%
Critical value = 3.84
Chi-square value=11.54
11.54 > 3.84 → Reject H_0
Conclusion: Usage significantly influences participation.

Objective 3:

To identify key challenges and barriers that limit effective citizen engagement in e-governance systems.

Hypothesis

- **H_{03} (Null Hypothesis):** Challenges and barriers have **no significant impact** on citizen engagement in e-governance platforms.
- **H_{13} (Alternative Hypothesis):** Challenges and barriers have a **significant impact** on citizen engagement in e-governance platforms.

Observed Frequency Table

Barriers / Participants	Participate	Do not participate	Total
Face Barriers	8	17	25
No Barriers	16	9	25
Total	24	26	50

Expected Frequency Table

Formula: E = (Row Total × Column Total) / Grand Total

Barriers / Participants	Participate	Do not participate
Face Barriers	12	13
No Barriers	12	13

Chi-Square Calculation

Category	**O**	**E**	**$(O-E)^2/E$**
Barriers-Participate	8	12	1.33
Barriers- Do not participate	17	13	1.23
No Barriers - Participate	16	12	1.33
No Barriers- Do not participate	19	13	1.23

Calculated χ^2 value = 5.12
Degrees of Freedom
Degree of Freedom = (no. of rows − 1) (no. of columns− 1)
(3 − 1) (2 − 1)= **1**
Level of significance = 5%
Critical value = 3.84
Chi-square value=5.12
5.12 > 3.84 → Reject H_0
Conclusion: Barriers significantly affect participation.

Data Analysis and Interpretation

1.Awareness vs Usage of E-Governance Platforms
Chi-Square Test was used to analyze the connection between awareness and the use of e-governance by the citizens. The Chi-Square Test value calculated (χ^2 = 8.34) is higher than that from the table (3.84) at a 5% significance level with 1 degree of freedom.

Interpretation:

Since the calculated value exceeds the table value, the null hypothesis is rejected. This indicates that there is a significant association between awareness and usage of e-governance platforms. Citizens who are more aware of digital governance services are more likely to use them. This highlights the importance of awareness programs and digital literacy initiatives in improving the adoption of e-governance systems.

2. Usage vs Citizen Participation

Chi-Square Test was carried out in order to examine the connection between the utilization of e-governance tools and the involvement of citizens in smart city governance. The obtained Chi-Square statistic (χ^2 = 11.54) is higher than the critical value of 3.84 at the 5% level of significance.

Interpretation:

The null hypothesis is therefore rejected, meaning there is a strong correlation between usage and participation. It means that people who actively engage in e-governance tools are more likely to be involved in governance processes like giving feedback, making complaints, and participating in surveys.

Barriers vs Citizen Participation

The Chi-square test was applied to determine whether barriers affect citizen participation in e-governance systems. The calculated Chi-square value (χ^2 = 5.12) is greater than the table value (3.84).

Interpretation:

As the computed value exceeds the tabulated value, the null hypothesis is rejected, which means that barriers play an important role in shaping citizen participation. Some of the barriers include unawareness, illiteracy in terms of information technology, lack of access to the Internet, and security issues.

Overall Interpretation

As seen from the chi square test, awareness, usage, and barriers have a great effect on citizen participation in e-governance systems. While increased awareness promotes usage, high levels of usage promote participation. On the other hand, barriers tend to reduce participation. Hence, for successful implementation of e-governance and creation of a smarter city, it is important to boost awareness and reduce barriers.

Findings of the Study

1. The study reveals that a majority of respondents are aware of e-governance platforms, but a notable portion still lacks adequate awareness.
2. Awareness has a significant influence on the usage of e-governance platforms, indicating that higher awareness leads to increased adoption.
3. The usage of e-governance platforms among citizens is moderate, with an equal proportion of users and non-users, showing that awareness does not always translate into usage.
4. Citizen participation in smart city governance through digital platforms is relatively low, with many respondents not actively engaging despite the availability of such platforms.
5. There is a significant relationship between usage and participation, suggesting that citizens who use e-governance platforms are more likely to participate in governance activities.
6. Barriers such as lack of awareness, poor internet access, digital illiteracy, and concerns about privacy and security significantly affect citizen engagement.
7. The presence of these barriers reduces the effectiveness of e-governance platforms in promoting inclusive participation.
8. Overall, while e-governance platforms have improved service delivery and accessibility, their potential for enhancing active citizen participation is not fully realized.

Conclusion of the Study

1. The current research titled “Citizen Participation in Smart Cities through E-Governance Platforms: A Study of Hyderabad” reflects the increasing significance of e-governance in modern urban management. According to the results obtained during the course of the investigation, despite the fact that a significant proportion of the population has knowledge about e-governance platforms, the same cannot be said for their active use and citizen participation.

2. The statistical analysis confirms that awareness significantly influences the usage of digital platforms, and increased usage, in turn, enhances citizen participation. However, the overall level of participation remains moderate, suggesting that e-governance platforms are still primarily used for service delivery rather than for active civic engagement and decision-making. The study also identifies several critical barriers, including digital illiteracy, limited internet access, lack of trust, and privacy concerns, which hinder effective participation.
3. 3. In addition, the findings suggest that demographic characteristics such as age play a role in participation rates, underscoring the importance of adopting a strategy to mobilize various segments of the citizenry. While e-governance programs have enhanced transparency, efficiency, and access to public services, they have not fully tapped into their capacity to promote participative governance.
4. Conclusively, for smart cities such as Hyderabad to enjoy the full benefits of digital transformation, there is need to shift from being technology-led to having a more people-oriented approach. This involves increasing awareness, increasing digital literacy, making access possible, and fostering citizens' trust. Improving these areas will contribute to good governance of the city, leading to its sustainable growth as a smart city.

Suggestions / Recommendations

Based on the findings of the study, the following recommendations are suggested to improve citizen participation in e-governance platforms:

1. **Enhance Awareness Programs**: Government authorities should conduct regular awareness campaigns through social media, workshops, and community programs to educate citizens about available e-governance services.
2. **Improve Digital Literacy**: Training programs should be organized, especially for elderly and less-educated groups, to improve digital skills and confidence in using online platforms.
3. **Strengthen User-Friendly Platform:** E-governance portals and mobile applications should be made more **simple, accessible, and multilingual** to ensure ease of use for all citizens.
4. **Improve Internet Accessibility**: Efforts should be made to enhance internet infrastructure and provide affordable access, especially for economically weaker sections.
5. **Ensure Data Privacy and Security**: Strong security measures should be implemented to protect user data and build trust among citizens in using digital platforms.
6. **Encourage Active Participation**: Authorities should create interactive features such as online surveys, feedback systems, and participatory decision-making tools to promote citizen engagement.
7. **Decentralize Governance Systems**: Reducing excessive centralization and empowering local bodies can improve direct citizen involvement in decision-making processes.
8. **Targeted Strategies for Different Groups**: Special initiatives should be designed for different age groups and communities to increase inclusiveness in participation.
9. **Continuous Monitoring and Feedback Mechanism**: Regular evaluation of e-governance platforms and incorporation of citizen feedback can help improve service quality and participation levels.
10. **Collaboration with Private and Community Organizations**: Partnering with NGOs, educational institutions, and private organizations can help in spreading awareness and improving implementation.

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MACHINE LEARNING-BASED BRAIN-VISUAL-AUDIO DECODEING WITH ELECTROENCEPHALOGRAPHY AND CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT: The Brain-Visual-Audio (BVA) Dataset is a multimodal dataset that combines EEG brain signals with synchronized visual and audio stimuli, enabling effective neural decoding and analysis of human cognitive responses. In this project, a machine learning-based system is developed to classify brain activity by utilizing these multimodal inputs. EEG signals are pre-processed using bandpass filtering and normalization to remove noise and artifacts, ensuring better signal quality. Visual features are extracted using pretrained Convolutional Neural Network (CNN) models such as ResNet50 and Efficient Net, while audio features are obtained using techniques like Mel-Frequency Cepstral Coefficients (MFCC) and spectrogram analysis.

These features from different modalities are then aligned and fused into a single unified dataset using feature fusion techniques. The combined feature set is used to train models such as Random Forest and Deep Neural Networks (DNNs) for accurate classification of cognitive states. The system generates predictions along with confidence scores, improving reliability. This approach has applications in Brain-Computer Interfaces (BCI), cognitive neuroscience, and assistive technologies, while also addressing challenges like handling complex data and improving model performance.

Keywords – EEG Signal Processing,

Multimodal Learning, Convolutional NeuralNetworks (CNN), Mel-Frequency Cepstral Coefficients

(MFCC), Feature Fusion, Random Forest, Deep
Neural Networks (DNN), Brain-Computer Interface (BCI), Neural Decoding, Cognitive State Classification.

I.INTRODUCTION

The rapid advancement of neuroscience and artificial intelligence has enabled better understanding of human brain activity. Brain-
Computer Interface (BCI) systems allow direct
communication between the brain and external devices, with Electroencephalography (EEG) being widely used due to its non-invasive nature and high temporal resolution. However, EEG signals are complex and noisy, making decoding difficult. Machine learning and deep learning techniques, especially Convolutional Neural Networks (CNNs), help extract meaningful patterns and improve accuracy.

Multimodal learning combines EEG with visual and audio data to better analyze cognitive processes. The Brain-Visual-Audio (BVA) dataset integrates these modalities, allowing classification of brain responses to combined stimuli. EEG signals are pre-processed using filtering and normalization, while visual features are extracted using models like ResNet50 and EfficientNet, and audio features using MFCC and spectrograms. These features are fused into a unified representation for analysis.

Machine learning models such as Random Forest and Deep Neural Networks (DNNs) are used to classify cognitive states and generate confidence scores. This system has applications in BCI, cognitive neuroscience, and assistive technologies. Although effective, challenges like data complexity, variability, and computational cost remain.

The proposed system focuses on efficient feature extraction, proper alignment of multimodal data, and accurate classification of brain responses. By integrating EEG, visual, and audio inputs, it improves prediction performance and provides better insight into human cognitive behavior. This approach also supports real-time analysis and can be extended to various practical applications, making it a scalable and adaptable solution for future research.

II.I. PRELIMINARIES

1.Electroencephalography (EEG) – It is a non-invasive neuroimaging technique used to record electrical activity of the brain through electrodes placed on the scalp. EEG signals reflect neural activity over time and are widely used in Brain-Computer Interface (BCI) systems due to their high temporal resolution. However, these signals are often noisy and require preprocessing techniques such as filtering and normalization to remove artifacts and improve signal quality.

2.Brain-Computer Interface (BCI) – It is a system that enables direct communication between the human brain and external devices by interpreting neural signals. BCI systems analyze brain activity and translate it into commands for applications such as assistive technologies, cognitive monitoring, and human-computer interaction. These systems rely heavily on accurate decoding of EEG signals using machine learning algorithms.

3.Convolutional Neural Network (CNN) – It is a deep learning model designed to automatically extract hierarchical features from data, especially images and spatial information. CNNs use convolutional layers to capture patterns such as edges, textures, and complex structures. In this project, pretrained CNN models like ResNet50 and EfficientNet are used to extract high-level visual features from images or video stimuli associated with brain responses.

4.Mel-Frequency Cepstral Coefficients (MFCC) – It is a feature extraction technique used in audio signal processing to represent the short-term power spectrum of sound. MFCC captures important frequency characteristics based on human auditory perception, making it suitable for analyzing audio stimuli. These features are widely used in speech recognition and audio classification tasks.

5.Feature Fusion – It is the process of combining features extracted from multiple data sources into a single unified representation. In multimodal systems, feature fusion integrates EEG, visual, and audio features using techniques such as concatenation and alignment. This helps in capturing relationships between different modalities and improves the performance of classification models.

6.Random Forest Algorithm – It is an ensemble machine learning method that builds multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting. Each tree is trained on a subset of the data, and the final prediction is made based on majority voting or averaging. It is widely used for classification tasks due to its robustness and efficiency.

7.Deep Neural Networks (DNN) – It is a class of machine learning models consisting of multiple layers of interconnected neurons that learn complex patterns from data. DNNs are capable of modeling non-linear relationships and are used for classification and prediction tasks in high-dimensional datasets such as multimodal neural data.

8.Multimodal Learning – It refers to the integration and processing of multiple types of data such as EEG signals, visual inputs, and audio stimuli to improve learning and prediction performance. By combining different modalities, the system can achieve a more comprehensive understanding of cognitive processes compared to single-modal approaches.

9.Neural Decoding – It is the process of interpreting brain signals to infer cognitive states, intentions, or perceptions. Neural decoding involves applying machine learning techniques to EEG data to classify brain responses based on external stimuli such as images and sounds.

10.Bandpass Filtering – It is a signal processing technique used to retain frequencies within a specific range while removing unwanted low-frequency drift and high-frequency noise. In EEG preprocessing, bandpass filters (e.g., 0.5–50 Hz) are applied to enhance relevant brain signal components and improve analysis accuracy.

II.II. USER PROFILE ATTRIBUTES

User modeling plays a crucial role in adaptive systems, as it enables the system to personalize its behavior based on individual learner characteristics. In this work, a set of learner profile attributes is considered to enhance the effectiveness of the proposed machine learning framework. The primary objective is to improve the accuracy of cognitive state classification by aligning system outputs with user-specific factors, thereby making the system more adaptive and efficient. By incorporating these attributes, the model can better understand variations in brain responses and provide more meaningful interpretations, ultimately improving system performance and user engagement.

1.Cognitive State Level – This refers to the current mental or cognitive condition of the user while interacting with stimuli. Similar to hierarchical learning models, different levels of brain responses can be identified, ranging from basic perception to higher-level reasoning and decision-making. These levels include signal awareness, pattern recognition, active processing, analytical thinking, and response evaluation. Understanding these levels helps in classifying EEG signals more accurately.

2.Stimulus Interaction Preference – This represents how a user responds to different types of sensory inputs such as visual and auditory stimuli. Some individuals may respond more strongly to visual content, while others may show higher sensitivity to audio inputs. Identifying these preferences helps in improving feature relevance during multimodal fusion and enhances classification performance.

3.Data Recording Duration – This includes the duration for which EEG signals and corresponding stimuli are recorded. It indicates the time span of user interaction and plays a role in capturing sufficient brain activity patterns. Proper time segmentation ensures better feature extraction and improves model reliability.

4.Preferred Stimulus Format – Due to variations in perception, users may respond differently to various formats such as images, videos, or audio clips. The system considers multiple formats including static images, dynamic video sequences, and audio signals to capture diverse brain responses. This helps in building a more generalized and adaptable model.

In addition to these explicit factors, implicit factors such as user attention level, engagement, and consistency of responses can also be analyzed during system operation. These factors provide deeper insights into brain activity patterns and help refine the model over time. By integrating both explicit and implicit attributes, the proposed system aims to achieve more accurate and personalized neural decoding, improving its applicability in real-world scenarios.

II.III. CHALLENGES AND MOTIVATION

Although technology alone cannot fully solve complex challenges such as accurately interpreting human brain activity, it can significantly enhance the quality and effectiveness of solutions in neural decoding systems. This serves as the motivation behind our work.

1.A major challenge in multimodal neural decoding systems is the reliance on limited features, often focusing only on raw EEG signals or isolated modalities such as visual or audio data. This can lead to incomplete understanding and reduced classification accuracy. However, brain responses are influenced by

multiple factors, including the type of stimulus, temporal alignment, and individual variability. To address this, our approach incorporates multiple dimensions such as EEG, visual, and audio features into a unified framework. Since these modalities do not have a direct one-to-one relationship and labeled multimodal datasets are limited, there is a need to effectively integrate and learn from these heterogeneous data sources. The proposed system addresses this issue by using machine learning techniques to extract, align, and fuse multimodal features, thereby improving the accuracy and robustness of cognitive state classification.

2.Another key challenge in applying machine learning to this domain is handling the diversity and complexity of data types. While EEG signals can be processed numerically, visual and audio features often exist in high-dimensional and unstructured forms. Additionally, aligning these modalities in time and extracting meaningful relationships between them is not straightforward. Traditional similarity measures such as Euclidean distance or correlation are not always effective in capturing complex multimodal relationships. Therefore, there is a need for advanced feature extraction and fusion techniques that can transform heterogeneous data into a compatible format. The proposed system overcomes this limitation by using deep learning models for feature extraction and applying fusion strategies to create a unified representation, enabling more accurate and meaningful classification outcomes.

III. METHODOLOGY

Our methodology for neural decoding consists of selecting high-quality multimodal data samples where EEG signals are properly synchronized with visual and audio stimuli, and ensuring that the data meets predefined thresholds for reliability. We then establish relationships between features extracted from EEG, visual, and audio modalities, followed by grouping similar patterns of brain responses using machine learning techniques to identify clusters of cognitive states, and finally using the most dominant and frequently occurring feature patterns as informative representations for accurate classification and prediction of brain activity.

III.I. HYPOTHESIS

In order to design an effective framework for multimodal neural decoding and address the key research question—how to establish meaningful relationships between EEG signals, visual inputs, and audio stimuli for accurate cognitive state classification—we formulate our research hypothesesas follows:
H1: Brain responses, apart from being interpreted solely through EEG signals, can be more effectively classified by incorporating synchronized visual and audio features.
H2: Integrating multimodal data with machine learning models leads to more accurate, reliable, and interpretable cognitive state predictions.

Let ‘S’ be a system.
$D = \{d_1, d_2, d_3, \ldots, d_m\}$ be a set of multimodal data samples.
$U = \{u_1, u_2, u_3, \ldots, u_n\}$ be a set of subjects/users.
$A = \{a_1, a_2, a_3, a_4, a_5\}$ be a set of feature attributes.
$C = \{c_1, c_2, c_3, \ldots, c_k\}$ be a set of cognitive states (classes).

where
$m, n \in \mathbb{N}$
$a_1 \rightarrow$ EEG signal features (processed signals)
$a_2 \rightarrow$ visual features (extracted using CNN models)
$a_3 \rightarrow$ audio features (extracted using MFCC/spectrogram)
$a_4 \rightarrow$ temporal alignment (synchronization between modalities)
$a_5 \rightarrow$ feature fusion representation

$p_{ij} \rightarrow$ feature value of sample d_i for attribute a_j ($i = 1$ to m, $j = 1$ to 5)
$c_i \rightarrow$ predicted cognitive state for sample d_i

Problem Statement:

$\forall\, d_i \in D$, classify d_i into a cognitive state $c_i \in C$ using the combined multimodal feature set A.

III.II. SOLUTION & APPROACH FOLLOWED

Step 1 – Alg. "build_data_subset"
input – multimodal dataset
output – subset of data samples based on quality threshold criteria

a.
$\forall\, d_i \in D$ build $V \subseteq D \mid q_i \geq \delta_0$, $\delta_0 \leq 1$ and $\delta_0 \in \mathbb{R}$ (i = 1 to m) /*build high-quality data subset*/

b.
$\forall\, d_i \in V$, consider f_{ij} as a point in k-dimensional feature space (i = 1 to m, j = 1 to k)

In this step, from the entire dataset, we select only those samples that satisfy a predefined quality threshold (for example, signals with low noise or strong synchronization between EEG, visual, and audio inputs). This subset represents reliable data samples suitable for further processing. The threshold value is tuned to ensure that the subset is sufficiently large while maintaining data quality. Each selected sample is then represented as a feature vector in a high-dimensional space formed by multimodal attributes.

Step 2 – Alg. "multimodal_features_quantify"
input – multimodal feature parameters (EEG, visual, audio)
output – unified numerical representation of features

$\forall$ feature attributes (a_1, a_2, a_3)

a. Construct matrix A where each row and column represent feature parameters from different modalities, and A_{ij} = correlation or similarity between feature i and j.

b. Apply factorization technique to split A into B & C:
$A_{n\times n} = B_{n\times k} \times C_{k\times n}$
where $C_{k\times n}$ → feature representation matrix (rows = extracted features, columns = original parameters), and C_{ij} = contribution of each parameter to extracted features,
and $B_{n\times k}$ → weight matrix (rows = parameters, columns = features), and B_{ij} = importance of each feature for a parameter.

c. Now,
(i) $\forall$ rows in B,
A. Consider maximum(value).
B. Choose corresponding feature row in C.
C. Obtain an ordering that defines the importance of each feature across modalities.
D. Construct matrix D where each row represents one such ordering.

(ii) Make matrix D symmetric by replacing D_{ij} with minimum(D_{ij}, D_{ji}).

(iii) $\forall$ rows in D, take average score
(Each average value represents the normalized numerical value of multimodal features).

In this step, heterogeneous features from EEG, visual, and audio data are transformed into a unified numerical form. This enables effective comparison, fusion, and usage in machine learning models for accurate cognitive state classification.

Secondly, we apply feature factorization techniques to extract meaningful patterns from multimodal attributes. This process identifies how much importance each feature (EEG, visual, and audio) holds with respect to others in terms of weights. Since heterogeneous features cannot be directly compared using

simple numerical metrics, we construct a similarity matrix and make it symmetric to ensure consistency in relationships. The average of each linear ordering in this matrix represents the overall similarity among features. Thus, the output of this step is a normalized numerical representation of multimodal features, which can be effectively used in subsequent stages.

Step 3.1 – Alg. "group_data"
This step focuses on grouping multimodal data samples based on similarity in feature space.
input – data points for each sample, with coordinates representing extracted multimodal features
output – cluster with largest number of similar samples

$S \rightarrow \{\phi\}$
Pick first point f_{ij} at random
$S \rightarrow S \cup \{f_{ij}\}$
$n = 1$
choose a value $k \in \mathbb{N}$ /*k = number of clusters*/

while $n \leq k$
{
Add point q' to S, such that
$q' \in f_{ij}$ and $\min\{\text{distance}(q', S)\} > \text{distance}(q_i, S)$
$(q_i \in f_{ij} - q', i = 1 \text{ to } m, j = 1 \text{ to } k)$

$S \rightarrow S \cup \{q'\}$
$n = n + 1$
}

Step 3.2
While any point has changed in cluster made:
/*K-nearest neighbour based clustering*/

{
$\forall f_{ij}$ $(i = 1 \text{ to } m, j = 1 \text{ to } k)$
$\forall S_a \in S$ $(a = 1 \text{ to } k)$

$d(S_a, f_{ij}) = \sqrt{[(S_1 - f_1)^2 + \ldots + (S_k - f_k)^2]}$ /*Euclidean distance*/

$x[a] = \min\{d(S_a, f_{ij})\}$
get $l = a$ which corresponds to $\min(x[])$
$S_l = S_l \cup f_{ij}$

$\forall$ every S_l, calculate mean of points (M) in that cluster
}

Step 3.3
Reduce 'k' till average diameter D increases significantly
/*optimal number of clusters*/

$D = \max(d(p, q))$
$\forall (p, q) \in f_{ij}$

Step 3.4
Choose cluster with largest number of data samples
$C \leftarrow \max\{\text{Size}(S_a)\}$

This clustering process groups similar brain response patterns based on multimodal features. The largest cluster represents dominant cognitive patterns and serves as a strong indicator of common neural responses.

Step 4 – Alg. "frequent_features_filter"
This step identifies the most dominant feature patterns from the largest cluster.
input – data points of the largest cluster
output – most frequently occurring feature combinations

Choose support level $sl \in \{0,\ldots,1\}$ and $sl \in \mathbb{R}$
/association analysis/

$L_1 \leftarrow \{1\ \text{itemset}\}$

for ($k = 2, L_{k-1} \neq \phi, k{+}{+}$)
{
$c_k \leftarrow \{c \mid c = a \cup \{b\} \wedge a \in L_{k-1} \wedge b \in L_{k-1} \wedge b \notin a\}$

$\forall\ t_i \in C$
{
$c_t \leftarrow \{c \mid c \in c_k \wedge c \subseteq t_i\}$

$\forall\ c \in c_t$, c.count++
}

$L_k \leftarrow \{c \in c_k \mid c.count > sl\}$
}

return $L = \bigcup L_k$

In this final step, association analysis is applied to extract frequently occurring feature combinations using the Appropriate principle. A minimum support level is defined to filter significant patterns. The most frequent feature set represents dominant multimodal characteristics, which are then used for accurate classification and interpretation of cognitive states.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The main contribution of our work is the application of machine learning techniques to develop an efficient multimodal neural decoding system that improves the accuracy of cognitive state classification. The strength of the system lies in its ability to integrate EEG signals with visual and audio data, providing a more comprehensive understanding of brain activity. Instead of relying only on a single data source, the system generates predictions in the form of "Brain responses with specific EEG patterns, visual features, and audio characteristics are classified into a particular cognitive state with a given confidence score." The advantages are:

1. Improved accuracy and reliability due to multimodal data integration.
2. Better interpretation of brain activity by combining complementary features.
3. Increased robustness against noise and variability in individual data sources.
4. Enhanced applicability in real-time systems and practical scenarios.

For implementation, we used the Brain-Visual-Audio (BVA) dataset, which contains synchronized EEG, visual, and audio data samples. Since real-world datasets with perfectly aligned multimodal features are limited, preprocessing and feature extraction techniques were applied to standardize the data. EEG signals were filtered and normalized, while visual and audio features were extracted using deep learning and signal processing methods. These features were then fused and used to train models such as Random Forest and Deep Neural Networks, leading to improved classification performance and reliable prediction outcomes.

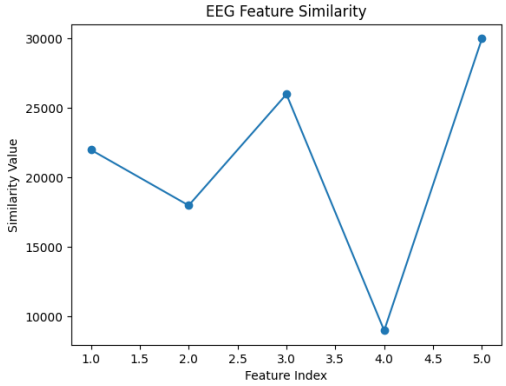

Fig (i) EEG Signal Feature Analysis

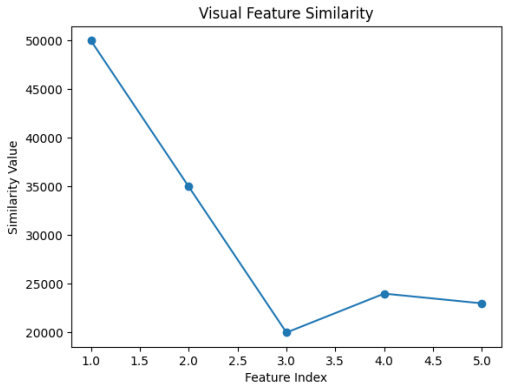

Fig (ii) Visual Feature Extraction Analysis

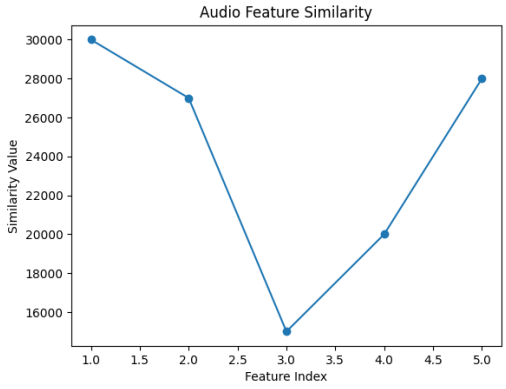

Fig (iii) Audio Feature Extraction Analysis

From Fig (i) and Fig (ii), we infer that certain multimodal features show stronger relationships compared to others. In the EEG feature graph, feature indices 3 and 5 exhibit higher similarity values, indicating that they are more closely related and play a significant role in representing brain activity, while feature index 4 shows the least similarity compared to others. Similarly, in the visual feature graph, features 1 and 2 show

relatively higher similarity, whereas feature 3 demonstrates lower similarity, indicating weaker correlation. In the audio feature graph, features 1 and 5 appear more similar, while feature 3 shows comparatively less similarity. These observations help in identifying dominant features that contribute more effectively to classification.

Evaluating such a system can be challenging due to the complexity of multimodal data and the absence of direct feedback mechanisms. Instead of relying solely on explicit evaluation, the system can be assessed through implicit inference, such as analysing prediction accuracy, confidence scores, and consistency of classification results across different samples. Although this approach may not directly measure user satisfaction, it provides a practical and efficient way to evaluate system performance with lower computational and operational cost.

Further, we grouped the subset of data samples that satisfied a predefined quality threshold and applied clustering techniques to identify patterns in multimodal feature space. Using visualization methods such as parallel coordinate plots, each feature is represented along a vertical axis, and each data sample is visualized as a line connecting these axes based on its feature values. Prominent patterns or overlapping lines indicate clusters of similar brain responses, which can be considered strong candidates for classification. Additionally, enhanced visualizations can represent data points within structured geometric layouts, reflecting relationships among features. Since the clustering is based on multiple attributes, such visual representations help in understanding complex interactions between EEG, visual, and audio features, ultimately supporting more accurate and interpretable neural decoding.

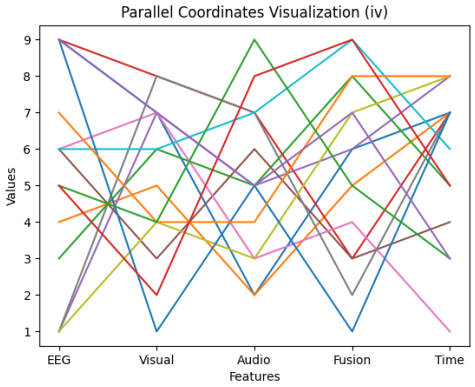

Fig (iv) Parallel Coordinates Visualization (Multimodal Features)

Next, after applying association analysis on the clustered multimodal data, we obtain meaningful feature patterns based on the most frequently occurring feature combinations. By keeping the support level constant at a defined threshold (e.g., 0.1), we generate representative feature tags for different data samples. If multiple feature combinations share similar frequencies, they can be grouped together to form a "feature cloud," where each cloud represents more than one dominant pattern. These feature tags help in identifying consistent relationships between EEG, visual, and audio modalities.

Although some of the generated feature tags may not include all multimodal attributes, the system is expected to improve as more data samples are incorporated. As the dataset grows, the number of possible feature combinations increases, leading to more refined and higher-order patterns. This is because the proposed system follows a progressive learning approach, where performance improves with the availability of more data. Such an approach is well-suited for real-time and continuous learning scenarios, where new data is constantly generated.

Sample Data Instance – Feature Tags Generated
Sample 1 → [EEG_1, $Visual_2$, Time(20–30), $Feature_3$, $Feature_5$]
Sample 2 → [EEG_2, $Audio_3$, –, $Feature_4$, $Feature_2$] and [–, $Visual_1$, Time(40–50), $Feature_3$, $Feature_1$]

Sample 3 → [EEG_1, $Visual_2$, Time(50–60), $Feature_3$, $Feature_4$] and [EEG_2, $Visual_3$, Time(20–30), $Feature_2$, $Feature_4$]
Sample 4 → [–, –, –, $Feature_4$, $Feature_1$] and [–, $Audio_2$, Time(40–50), –, –]

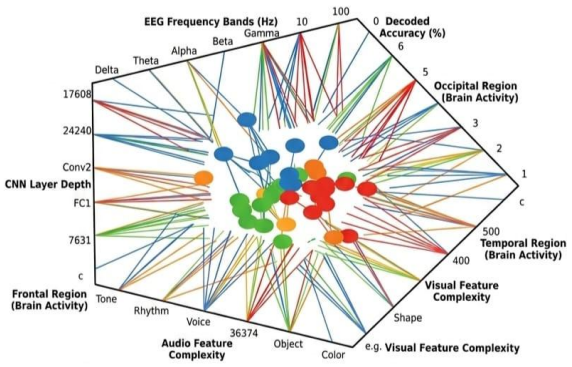

Fig (v) Feature Tags Generated for Multimodal Data (fields represent EEG features, visual features, time range, audio features, and fused feature patterns)

Sample ID	Feature Tag Generated
S1	[EEG_1, $Visual_2$, Time(40–50), $Feature_3$, $Feature_5$]
S2	[EEG_2, $Audio_3$, –, $Feature_4$, $Feature_2$] and [–, $Visual_1$, Time(50–60), $Feature_3$, $Feature_1$]
S3	[EEG_1, $Visual_2$, Time(50–60), $Feature_3$, $Feature_4$] and [EEG_2, $Visual_3$, Time(20–30), $Feature_2$, $Feature_4$]
S4	[–, –, –, $Feature_4$, $Feature_1$] and [–, $Audio_2$, Time(40–50), –, –]

In this section, we discuss prior studies related to neural decoding and multimodal systems. Earlier research has shown that relying only on single-modal data is insufficient for accurate interpretation. Studies indicate that ratings or isolated inputs alone cannot effectively capture complex patterns, leading to reduced performance.

Research in adaptive and intelligent systems highlights the importance of incorporating multiple factors such as user behaviour, contextual data, and interaction patterns to improve system accuracy. Instead of focusing only on algorithm optimization, integrating meaningful attributes and data representations significantly enhances performance.

Several works have also explored context-aware systems, considering factors such as time, activity, and user-specific characteristics. However, many implementations remain at a prototype level and do not fully utilize multimodal data. Key attributes such as prior knowledge, preferences, and behavioural patterns have been identified as important, but their integration into machine learning frameworks is still limited.

To the best of our knowledge, combining EEG, visual, and audio data using machine learning for cognitive state classification is still an emerging area. Hence, the proposed system contributes by leveraging multimodal feature integration and advanced learning techniques to improve accuracy and provide a scalable solution.

VI. CONCLUSION

In this paper, we have designed a solution to address the challenges in accurately interpreting and classifying brain activity using multimodal data. Inefficient or incomplete analysis of EEG signals can lead to incorrect predictions and reduced system reliability. This affects the overall performance of neural decoding systems and limits their practical usability. We consider this domain significant because brain signals vary greatly across individuals, and understanding them requires the integration of multiple data sources such as visual and audio stimuli. Due to the complexity and scale of such data, manual analysis or traditional methods are insufficient. Therefore, intelligent machine learning approaches are required to effectively combine multimodal features and capture meaningful patterns. By leveraging EEG, visual, and audio attributes, the proposed system aims to model real-world cognitive behavior more accurately and improve the performance, reliability, and interpretability of neural decoding systems.

VII. FUTURE WORK

For future work, we aim to improve the multimodal neural decoding system by exploring advanced models and better feature fusion techniques. We plan to test the system on larger and more diverse datasets to enhance accuracy and generalization.

Further work will focus on optimizing feature selection and tuning model parameters to reduce complexity and improve performance. We also aim to analyse model behaviour using different evaluation metrics and confidence levels for better reliability.

Additionally, extending the system to real-time applications, improving data preprocessing methods, and developing well-labelled multimodal datasets will enhance scalability and practical usability.

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CROP DISEASES PREDICTION

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ABSTRACT

Timely identification of plant diseases is essential for maintaining crop quality and agricultural productivity. Conventional manual inspection methods are often slow, inconsistent, and dependent on expert knowledge. This paper presents a deep learning-based Crop Disease Prediction System that automatically identifies plant diseases from leaf images.

The proposed system integrates image preprocessing, feature extraction, and Convolutional Neural Networks (CNN) to classify plant conditions accurately. In addition to disease detection, the system provides actionable recommendations such as suitable treatments and preventive measures.

Experimental evaluation demonstrates that the system achieves reliable prediction accuracy and supports real-time decision-making. This approach contributes to improving agricultural efficiency and reducing crop losses.

1. INTRODUCTION

Agriculture remains a fundamental sector influencing both economic stability and food security. One of the major challenges faced by farmers is the early detection of plant diseases, which can significantly affect crop yield and quality. Traditional detection techniques rely heavily on visual inspection, making them time-intensive and prone to human error.

Recent advancements in Artificial Intelligence, particularly in deep learning, have enabled automated image-based analysis. Convolutional Neural Networks (CNNs) are especially effective in recognizing patterns in images, making them suitable for plant disease classification.

This study proposes an intelligent system capable of analysing leaf images and providing instant diagnostic results along with treatment suggestions, thereby assisting farmers in taking timely action.

2. LITERATURE SURVEY

Several researchers have explored the use of machine learning and deep learning techniques for plant disease detection.

Earlier work using CNN-based models demonstrated high classification accuracy when trained on controlled datasets; however, performance often declined under real-world environmental conditions. Comparative studies of deep learning architectures have shown improved results but require large, well-labeled datasets and significant computational resources.

Transfer learning approaches have been introduced to address data limitations, enabling faster training and improved efficiency. Additionally, real-time detection systems have been developed, though challenges remain in identifying early-stage infections due to subtle visual differences.

Despite these advancements, many existing systems lack practical usability, real-time responsiveness, and user-friendly interfaces, especially for farmers without technical expertise.

3. PROPOSED METHODOLOGY

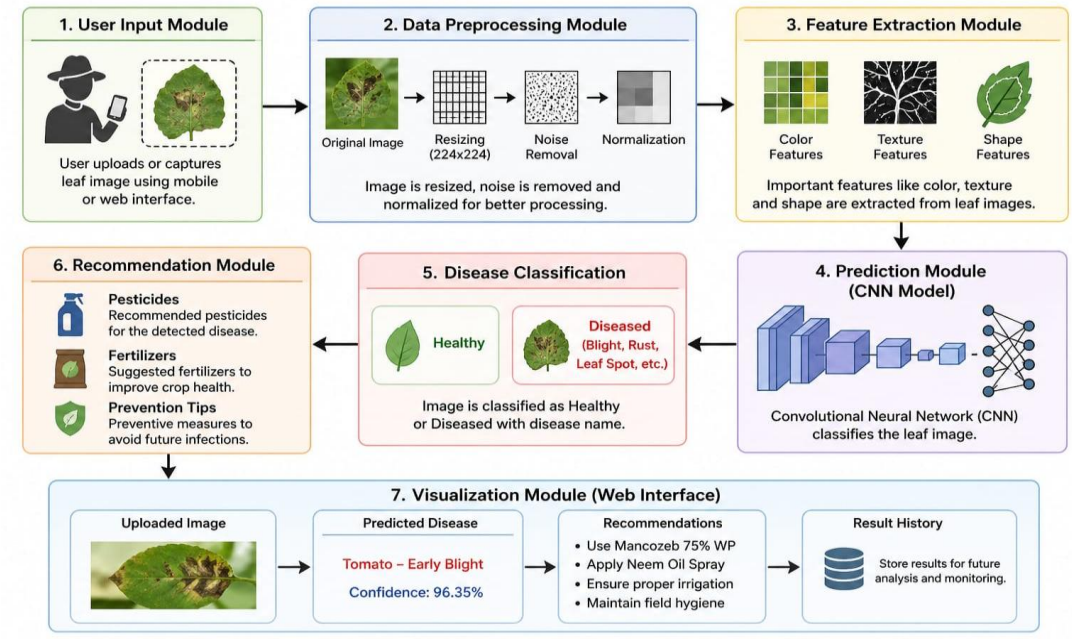

Figure 1: System Architecture of Crop Disease Prediction System

3.1 System Architecture

The proposed system is designed as a multi-stage pipeline consisting of the following modules:

- **Input Module:** Captures leaf images through a mobile or web interface
- **Preprocessing Module**: Enhances image quality by resizing, noise reduction, and normalization
- **Feature Extraction Module**: Identifies relevant visual patterns such as color variations and texture
- **Prediction Module**: Utilizes a CNN model to classify the image
- **Recommendation Module**: Generates treatment suggestions and preventive measures
- **Visualization Module**: Displays results through a user-friendly interface

3.2 Algorithms Used

The system employs a Convolutional Neural Network (CNN) as the primary classification model due to its effectiveness in image recognition tasks.

Supporting techniques include:

- Image preprocessing for improved data quality
- Feature extraction for identifying disease characteristics
- Dataset splitting for proper training and evaluation
-

3.3 Working Process

The system follows a sequential workflow:

6. The user submits a leaf image
7. The image undergoes preprocessing
8. Relevant features are extracted automatically
9. The CNN model performs classification
10. The system outputs the disease type along with recommendations

4. EXPERIMENT AND RESULTS

The system was evaluated using a dataset of plant leaf images representing both healthy and diseased conditions.

Evaluation Metrics:

- Accuracy
- Loss
- Confusion Matrix

Observations:

- The model achieved strong classification performance
- Predictions were generated in real time
- The system effectively suggested treatment options

These results indicate that the proposed solution can assist in early disease detection and reduce dependency on manual inspection.

5. CONCLUSION

This paper introduces a deep learning-based system for automatic crop disease detection using leaf images. The integration of CNN models enables accurate classification, while the recommendation module provides practical guidance for disease management.

The system enhances agricultural decision-making by offering timely and reliable insights, ultimately contributing to improved crop productivity.

FUTURE WORK

Future improvements can focus on:

- Deploying the system as a mobile application
- Expanding the dataset to include more crop varieties
- Integrating advanced deep learning architectures
- Supporting real-time field-level detection

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Comparison of BLDC motor & BLDC Mono-shaft Hub Motor in Hybrid Scooter

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Abstract- This Paper Present a comparative study of BLDC Mono-shaft hub motor & conventional brush-less dc (BLDC) motor used for hybrid scooter application this study focus on working principle, maintenance requirement, structural design, performance characteristics. Conventional BLDC Motor require mechanical transmission system such as chains or belt, which introduce additional losses & maintenance requirement. In contrast, BLDC Mono-shaft motor are directly integrated into the Wheel, eliminating transmission losses & simplifying the overall system design. The comparison highlights that motor offer higher efficiency compactness, & lower maintenance while conventional BLDC motor provide better torque control & performance flexibility the analysis in selecting the appropriate motor type based on application requirement such as cost, efficiency, system complexity

Keywords- " BLDC Motor, Monoshaft Hub Motor, Hybrid Scooter, Electric Vehicle, efficiency, Direct Drive."

I.INTRODUCTION

With the increasing demand for energy efficient & eco-friendly transportation system, Electric & Hybrid Vehicles are gaining significant important. Among various motor technologies, the brush-lessDc (BLDC) motor has emerged as a preferred choose due to its high efficiency, compact size & long operation life. BLDC Motor are widely used in Electric motor, Hybrid vehicle.

In hybrid scooter system two major types of BLDC Motor configuration are commonly used the conventional BLDC Motor (mid drive system) & the BLDC Mono-shaft Motor. The conventional motor is mounted separately & transmit power to the wheel using mechanical component such as chain, belts or gears. On the other hand the hub motor is directly mounted inside the wheel, eliminating the need for external transmission system. The fundamental difference affects performance, efficiency maintenance & overall system design.

This paper aim to provide a detailed comparison between this to motor types to identify their advantages, limitations & suitability for hybrid scooter applications.

II.NEED OF WORK

In modern transportation system, specially in hybrid scooter, there is in increasing demand for improved energy efficiency, reduced emission & enhanced performance. Conventional scooter relying only on internal combustion engine suffer from high fuel consumption & environmental pollution. Although electric system offer a cleaner alternative challenges such as limited range, efficiency losses & maintenance issues still exist. In hybrid scooter design the choice between the conventional BLDC mono-shaft hub motor plays a crucial role ion determining overall system efficiency, cost, & reliability.

However, there is a lack of clear comparative analysis to guide proper motor selection based on application requirement. Additionally mechanical losses in conventional system & thermal & torque limitation in hub motors create the need for detailed evaluation. Their for this work is necessary to analysis compare both motor technologies helping the development of optimized hybrid scooter that achieve battery efficiency, lower maintenance & improved performance.

III. PROBLEM DEFINATION,AIM & OBJECTIVES

i.Problem Definition :-

In hybrid scooter system, efficient power management & motor selection are critical challenges. Conventional BLDC motor evolve mechanical transmission system such as chain or belt, which introduce energy losses increase maintenance requirement & overall system efficiency. On the other hand, BLDC hub motor eliminate transmission losses but face issues such as limited torque output, heat dissipation problem, & increased unspring weight. Due to this limitation, it becomes difficult to select the motor most suitable configuration for achieving optimal performance, efficiency, reliability. Additionally, there is lack of Proper comparative analysis to clearly understand the advantages & drawbacks of both motor types in hybrid application. This creates a need for a Systematic. Study to evaluate & identify the best solution for hybrid scooter system.

ii.Aim :-

To perform a detailed comparative analysis of conventional BLDC motor and BLDC mono-shaft hub motor to determine their suitability for hybrid scooter application. the study focuses on improving efficiency, reducing losses, and selection an optimal motor configuration for enhanced system performance.

iii.Objectives :-

1) To study the working principle and construction of conventional BLDC motor and hub motor.
2) To compare performance parameter such efficiency, torque and power output.
3) To identify advantages and limitations of each motor type.
4) To evaluate the impact of power selection on hybrid scooter performance.

IV.LITERATURE REVIEW

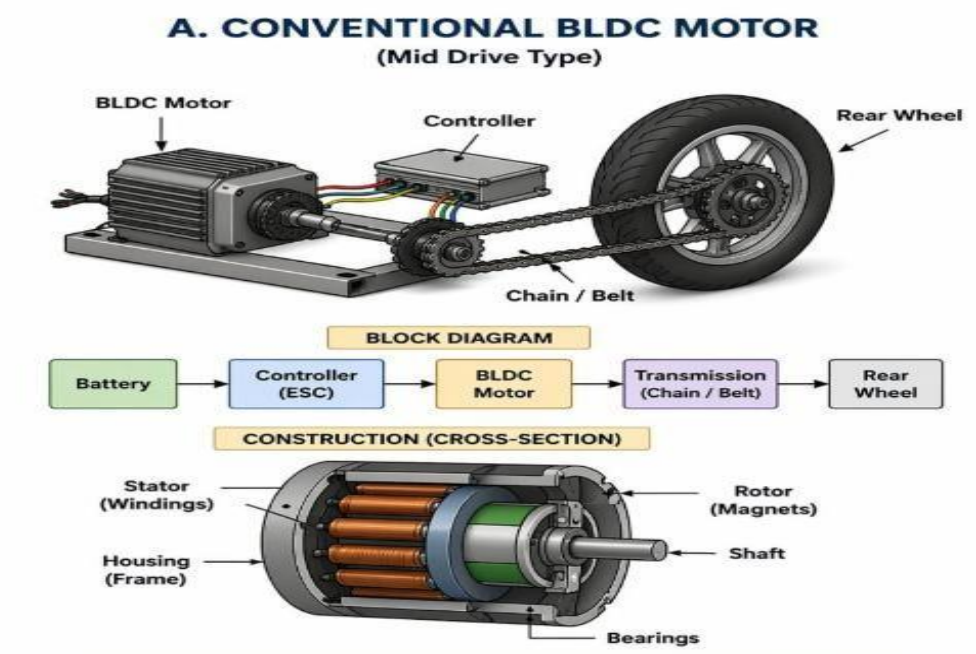
Shivanand Pal, Akshit Patel, Gaurav Sahu[1], many researchers have focused on improving hybrid scooter & electric two wheeler system to achieve higher efficiency, reduced emission & better performance. Studies highlights the use of BLDC motor Due to their high efficiency, compact size, & low maintenance, lithium ions batteries are widely preferred for their high energy density and longer life cycle. Research on hub motors shows Smoother operations & simplified design due to direct drive. Advanced control technique such as PID, fuzzy logic, genetic algorithms improve speed controls & system stability. Additionally regenerative breaking & DC to Dc converter plays a vital role in energy management, enhancing overall efficiency & reliability of hybrid scooter system.

Vishnu Sidharthan P,Yashwant Kashyyap[2],Recently studies on electric vehicle drives emphasize growing importance of Brush-less Dc (BLDC) motors due to their high efficiency, compact size, and low maintenance requirement. Research highlight that conventional DC and induction motors suffer from drawbacks such as wear, lower efficiency at varying load & large size, leading to increased interest in BLDC technology. Several works focus on advanced control strategies, including pulse with modulation (PWM) & closed loop speed control using micro-controller, to achieve precise torque & speed regulation. Mathematical modeling & simulation using tools like MATHLAB/Simulink have been widely adopted to analyze motor performance. Additionally, hardware implementation using controllers such as ATmega328 demonstrate practical feasibility. However, remain key research areas for improving overall drive performance & efficiency.

Miroslav Marcovic, Patrik Ragot & Yves Perriard [**3**], The literature on Brush-less DC motor design emphasizes the importance of optimization techniques to improve efficiency & performance. Discusses the application of different optimization algorithm including gradient based, direct search & genetic algorithm for slot-less BLDC Motor design. The study highlight that traditional optimization methods are highly depends on initial condition, while genetic algorithm provide better global search capability but require more computation time. A hybrid approach combining genetic & classical algorithms yields the best result by insuring both accuracy & convergence speed. Additionally, analytical model are widely used to their simplicity & ability to integrate with optimization tools, although numerical methods like finite element method(FEM) offer higher precision. Overall research indicates that combining advanced optimization techniques with analytical modeling significantly enhances BLDC Motor designs efficiency & reduce losses.

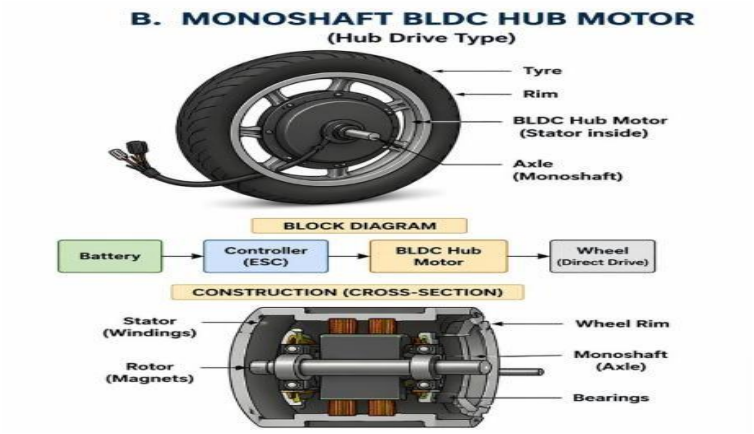
Mangaluru Satyandra Kumar Shet, Shripad T. Revankar [4], The literature highlights the growing importance of electric propulsion systems in light electric vehicles, particularly scooters. Studies focus on permanent magnet brush-less DC (PMBLDC) motors due to their high efficiency. Compact size, & superior torque speed characteristics. Finite element method (FEM) is widely used for motor design & performance evaluation, ensuring optimal efficiency & reduced torque ripple. Advanced control techniques such as field oriented control (FOC), direct torque control (DTC), & intelligent algorithm improve dynamic response & reliability. However, challenges remain, including high cost, research emphasizes subsystem level development, but lacks comprehensive integration approaches for overall electric vehicle performance optimization.

V.WORKING PRINCIPLE OF CONVENTIONAL BLDC MOTOR



A Conventional Brush-less DC (BLDC) motor is an electric motor in which the rotor, fitted with permanent magnets ,rotates inside a stat-or that carries three- phase winding's, and the mechanical output is taken through a rotating shaft connected to a transmission system such as a chain, belt or gearbox .the operating is based on the principle of electromagnetic induction, where an electronic controller supplies current in a specific, sequence to the stator winding's, creating a rotating magnetic field that interacts with the rotor magnets to produce torque. These motor are known for their high efficiency, good speed control ,and better heat dissipation due to external mounting. However, they require additional mechanical components for power transmissions, which increases complexity, maintenance, & energy losses.

VI.WORKING PRINCIPLE OF MONOSHAFT HUB BLDC MOTOR



In contrast, a mono-shaft hub BLDC motor is integrated directly into the wheel, where the stat-or is fixed to the axle and the outer rotor rotates along with the wheel, eliminating the need for any external transmission system. Its working is based on the Lorentz Force principle, where the interaction between the magnetic field and current carrying conductors produce motion. This design offers direct drive, compact structure, low maintenance, and higher overall efficiency since there are no transmission losses. However, it has limitations such as poor heat dissipation, increased wheel weight, and difficulty in maintenance or repair. Overall, conventional BLDC motors are more suitable for application requiring flexibility and high speed operation, while mono-shaft hub BLDC motors are ideal for electric scooter and lightweight electric vehicles due to their simplify and efficiency

VII. COMPARISON OF BLDC MOTOR AND HUB MOTOR

i.Structural Comparison

The conventional BLDC motor consists of a stat-or and a rotor assembly mounted on the vehicle chassis. Power is transmitted to the wheels through mechanical components. In contrast, the BLDC mono-shaft hub motor integrates the motor directly into the wheel hub ,where the rotor rotates along with the wheel and the stat-or remains fixed.

ii.Performance Comparison

Sr.No	Parameter	BLDC Motor(Conventional)	BLDC Monoshaft Hub Motor
1	Mounting	External (Chassis)	Inside wheel
2	Transmission	Chain/belt/Gear required	Direct drive
3	Efficiency	Moderate to High	High
4	Losses	Mechanical losses present	Minimal losses
5	Maintenance	High	Low
6	Installation	Complex	Simple
7	Torque Control	Better	Moderate
8	Cost	Moderate	Slightly higher

iii.Advantages and Disadvantage

Conventional BLDC Motor :

Advantages

- High torque capability
- Better control over speed and performance
- Suitable for heavy load applications

Disadvantages

- Transmission losses
- Require regular maintenance
- More complex design

BLDC monoshaft Hub Motor :

Advantages

- Compact and simple design
- High efficiency due to direct drive
- Low maintenance
- Reduced mechanical losses

Disadvantages

- Increased upsprung weight
- Heat dissipation challenges
- Limited torque compared to mid drive system

VI.APPICATION IN HYBRID SCOOTER

In hybrid scooter, the selection of the motor plays a vital role in achieving the desired balance between performance, fuel efficiency, and system reliability. Conventional BLDC motors are commonly used in hybrid system where higher torque and precise speed control are required. These motor are typically integrated with the drive-train through mechanical transmission system, making them suitable for applications where the internal combustion engine (ICE) and electric motor work together to deliver power under varying load condition. On the other hand BLDC mono-shaft hub motor are directly mounted inside the wheel, providing a simpler and more compact solution . They are ideal for light weight hybrid scooter where design simplicity, reduced mechanical losses & low maintenance are important factor although hub motor may offer slightly lower torque compared to conventional system, they significantly improve overall efficiency by eliminating transmission component, making them a preferred choice for cost effective & energy efficient hybrid scooter design.

VII. CONCLUSION

This paper presents a comparative analysis of conventional BLDC motor &BLDC mono-shaft hub motor used in hybrid scooter applications. It is observed that conventional BLDC motor offers superior torque control, flexibility, \& the better performance in high load conditions, making them suitable for system integrated with internal combustion engine. On the other hand, BLDC mono-shaft hub motor provide higher efficiency compact design, hybrid used due to the elimination of mechanical transmission component. Although hub motor phase challenges such as increased un-sprung weight & thermal limitation, they are highly effective for light weight & cost efficient scooter design. There for, the selection of motor type depends on specific application requirement such as performances, efficiency, cost & system complexity. Future advancement should focus on improving torque capability & heat management in hub motor to expand their use in hybrid vehicle system.

VIII. FUTURE SCOPE

Future research in hybrid scooter systems can focus on improving the efficiency & thermal managements of BLDC mono-shaft hub motors to enhance their performance under varying load conditions. The use of advanced control techniques, such as intelligent motor control algorithms & adaptive power management, can significantly optimize energy utilization. Additionally, the development of light weight & high strength materials can reduced overall vehicle weight & improving efficiency. Integration of smart system along with IOT based with monitoring can enable real time performance tracking, fault detection, & predictive maintenance their by increasing system reliability. Further advancement may also explore improved battery integration & regenerative breaking techniques. To maximize energy saving & extend the operational life of hybrid scooter.

REFRENCE

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VULNERABILITY AND PENETRATION TESTING – Deep Bug Hunter

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Abstract- Web applications are growing more and more complex as they integrate various frameworks, APIs, microservices. This increases the attack surface and it is more difficult to detect vulnerabilities by more traditional means of manual penetration tests. Most organisations have many independent security tools and as a result, have disjointed workflow and ineffective security testing processes. I have mentioned Deep Bug Hunter in this paper which is an automated web vulnerability-scanning framework which would be applicable in detecting some common security vulnerabilities e.g. SQL Injection (SQLi), Cross-Site Scripting (XSS) and configuration misconfigurations. The system integrates reconnaissance, endpoint discovery, vulnerability testing and automated report generation together in a single platform. The suggested framework applies automated crawling and vulnerability-injection testing in order to detect possible vulnerabilities in web apps. The type of experimental testing that has been carried out demonstrates that the automated scanning technique is far faster in terms of vulnerability detection time as compared to the manual testing techniques. Detailed vulnerability reports with severity score and proof-of-concept scripts are also produced by the system to help developers with remediation. The results show that the proposed system is more effective in the security testing and the vulnerability detection process is reduced. Deep Bug Hunter is an effective and user friendly security scanning tool which can be deployed by developers, students and security researchers..

Keywords: Web Security, Vulnerability Scanning, SQL Injection, Cross-Site Scripting, Automated Security Testing, Penetration Testi

I. INTRODUCTION

Web applications have become the foundation of the contemporary digital ecosystem, allowing a smooth interrelationship between users and services in a broad spectrum of areas, such as banking, e-commerce, healthcare, education, and government. As organizations are swiftly becoming digital, web-based platforms are increasingly being commissioned with the processing, storage, and transmission of extremely sensitive data like financial records, personal information, and confidential business transactions. As a result, a strong security of web applications has become not only a technical requirement but also a business and societal imperative. The architectural paradigm of the web applications has experienced a major shift in the past few years. Monolithic systems are being substituted with distributed and scalable designs like microservices, containerized deployments, and cloud-native systems. Moreover, the use of RESTful APIs and third-party integrations has led to a great level of interconnectivity between systems. These

improvements increase the flexibility, scalability, and performance but also make the application landscape more complex. It is complicated to create a larger attack surface, with several points of entry (APIs, hidden endpoints, misconfigured services, and so on) that adversaries can use to their advantage. This has made it even harder to detect and address the vulnerabilities in these dynamic environments. SQL Injection (SQLi), Cross-site Scripting (XSS), Cross-site Request Forgery (CSRF) and misconfigured security controls (poor authentication mechanisms and insecure HTTP headers) are among the most common security threats impacting web applications. These are always listed among the highest security risks by industry standard bodies like the Open Web Application Security Project (OWASP). The exploitation of such weaknesses may lead to dire consequences such as unauthorized access to databases, data leakage, session hijacking, and running of malicious scripts on client browsers. These vulnerabilities are still involved in spite of the secure coding practices and development frameworks because of the following reasons: poor input validation, security ignorance of the developers and the lack of security testing integration as part of the software development life cycle. The main traditional methods of vulnerability detection include the use of manual penetration testing that is performed by qualified security experts. Although manual testing offers thorough testing analysis and enables one to reveal intricate logic errors, it is nevertheless time-consuming, resource-intensive, and cannot be easily scaled in case of large and ever-changing applications.

In addition, the increasing use of agile and DevOps approaches requires quicker and more frequent security testing—manual approaches alone cannot sustain. To overcome these constraints, automated vulnerability scanners have been introduced, which offer quick and consistent evaluations. Nonetheless, current tools usually have a number of weaknesses, such as high cost of licenses, reduced adaptability and they tend to produce a high number of false positives. Most scanners use signature-based approaches to detection, only useful against known vulnerabilities, and incapable of detecting new vulnerabilities or those that depend on the context. Moreover, security practitioners often rely on a set of standalone tools to accomplish tasks like network reconnaissance, subdomain enumeration, crawling, and vulnerability exploitation. The result of such a fragmented approach is the disjointed workflows, complexity of the operations and the general lack of efficiency in the security assessment process. To address these issues, this paper offers a solution called Deep Bug Hunter, which is an integrated and automated model of web vulnerability testing that aims to offer a whole and scalable package to web application security in the present day. The proposed system is based on a modular, multi-phase structure that integrates smart reconnaissance, vulnerability detection based on behavior, automated validation, as well as in-depth reporting into one system. In contrast to traditional tools, Deep Bug Hunter focuses on the deep crawling model to reveal concealed endpoints, embedded forms, and API models, thus allowing a more comprehensive exploration of the application attack surface. The unique characteristic of the proposed framework is that it has a behavior-based vulnerability detection engine, which examines the response patterns of the application and not just using static signatures. The system can detect the slight changes in server response, which may be signs of vulnerability, by injecting well-formed payloads and tracking the changes. To further improve the accuracy of detection, it is possible to use data smoothing methods, like moving average filters, to cut the noise and ensure a lower number of false positive due to temporary network spikes or random server behavior. The other significant contribution of the work is that it incorporates an automated Proof of Concept (PoC) generation module that authenticates the identified vulnerabilities by producing exploit scripts, which can be executed.

This feature can link the gap between vulnerability detection and verification, and give the security professionals and developers tangible evidence of security vulnerabilities. Moreover, the system has a powerful reporting feature that creates detailed and actionable reports in various formats, such as PDF, HTML, and JSON. These reports allow the efficient communication between security teams and developers, allowing them to fix issues much faster and provide better security posture. The framework suggested is scalable, extensible, and user-friendly. It is architected in modules, which means that specific modules, like the crawler, the vulnerability engine, and the reporting module can be updated or extended separately, thus offering flexibility to new security threats and changing web technologies. Moreover, the system can be incorporated into the current DevSecOps pipelines that would allow conducting regular security tests during the software development life cycle and encourage an active vulnerability management approach. The main goals of this study are threefold: (a) the design and implementation of an automated and intelligent vulnerability scanning infrastructure, (b) to increase the efficiency, accuracy and scalability of web security testing, and (c) to deliver actionable and developer oriented vulnerability reports that can be used to quickly identify and address security vulnerabilities. This research will help provide a viable and efficient way of securing web applications in the current times by circumventing the shortcomings of the tools and methodologies available

II. RELATED WORKS

The assessment of web vulnerability and penetration testing is a huge and ever-changing industry and this

has resulted in the creation of numerous tools and frameworks that can be used to detect and provide solutions to security vulnerabilities in web applications. At the initial phases the methodologies were mostly based on manual penetration testing which involved security professionals undertaking methodical and thorough examination of applications with a view to identifying possible vulnerability. These techniques were very effective in detecting complex vulnerabilities, but were time-consuming in nature, highly skilled and lacked scalability when used to detect a large scale or highly dynamic web system.

As technology progressed, automated tools started to feature prominently in vulnerability assessment. Network reconnaissance tools like nmap have been widely applied to determine open ports, running services and system configurations to offer a background knowledge of the target environment. In the same manner, SQLMap has become a popular tool in the identification and exploitation of SQL injection weaknesses. Although these tools are very effective in their respective fields, they are utilized as autonomous tools, and manual coordination and result interpretation has to be carried out. This is not integrated making them ineffective when applied as part of a holistic vulnerability assessment.

Besides these tools, more web vulnerability scanners like Burp Suite and OWASP ZAP have been created to be able to detect common web-based vulnerabilities automatically. These tools have more sophisticated functionality such as proxy-based request interception, automated scanning, fuzz testing, and session management. Although they have strong potential, such tools tend to produce a high volume of false alarms, which require security analysts to verify them manually. Moreover, they are not yet effectively used in modern continuous integration and continuous deployment (CI/CD) pipelines, which lowers their performance in automated and continuous security testing settings.

The recent developments in the sphere have been aimed at enhancing the efficiency and accuracy of vulnerability detection by applying the intelligent methods, including machine learning, artificial intelligence, and behavioral analysis. These strategies are expected to examine the trends in the usage of web applications, identify abnormalities, and forecast the possible vulnerabilities before they can be used. Although these methods are quite promising, they need extensive datasets to train, parameterize models are frequently complicated, and can be incapable of the generalization across application architectures and environments. Consequently, their application in practice to real-world systems is still developing.

The other important shortcoming that has been noted in the current systems is the absence of end-to-end integration of the penetration testing lifecycle. The majority of tools available are tailored to a particular stage of reconnaissance, scanning, or exploitation, but do not offer a comprehensive framework which would allow all these options to seamlessly blend together. This discontinuity leads to a more complex testing process, inefficiencies, and a higher risk of overlooking key vulnerabilities as a result of the interphase gaps between various stages of analysis.

To overcome these issues, the Deep Bug Hunter framework is suggested as a single and automated solution, incorporating various elements into one unified pipeline. The system integrates smart reconnaissance, multi-threaded web crawling, vulnerability detection systems, and proof-of-concept (PoC) validation on a centralized design. This combined methodology not only enhances efficiency, but also allows a thorough coverage of the target application. One of its main distinguishing characteristics is the automated ability to generate PoCs, which verifies detected vulnerabilities prior to reporting, which greatly minimizes false positives and enhances reliability. Moreover, the system is scalable and flexible by design thus making it effective to support complex and large scale web applications. By being compatible with DevSecOps pipelines, it can be easily integrated into the current software development processes and support continuous and automated security testing over the course of the development cycle. By closing the gap between detection and validation, and offering a completely automated and integrated product, Deep Bug Hunter is a breakthrough in the domain of web vulnerability testing and penetration testing.

III. PROPOSED METHODOLOGY

Deep Bug Hunter is a comprehensive intelligent and fully automated web vulnerability scanning system that incorporates various phases of penetration testing in a single pipeline. The methodology focuses not only on detection but also on validation and prioritization of vulnerabilities to ensure that the results are accurate and actionable. The system architecture is layered where each module plays a particular role but still has a smooth communication with other modules. This hierarchical structure provides a scalable architecture to deal with large-scale web applications efficiently and in practical scenarios.

Reconnaissance and Information Gathering

Reconnaissance phase is the backbone of the whole vulnerability assessment process as it dictates the level and extent to which the analysis proceeds. Deep Bug Hunter in this stage carries out a large amount of information gathering to create a complete profile of the target web application. The system starts with subdomain enumeration via automated methods in order to reveal concealed or less noticeable domains belonging to the main target. This is important as attackers usually use vulnerabilities in subdomains that

are ignored.
In addition to this, the framework conducts multi-threaded port scanning, which enables the efficient probing of various ports at a time. This greatly cuts down scanning time as compared to the conventional sequential methods. The system also interprets network responses to identify service versions and configurations, which can indicate old or insecure parts.
Moreover, metadata about server technologies (e.g., web servers (e.g., Apache, Nginx), back-end programming language, frameworks, and content management systems) are reconstructed by analyzing the HTTP response headers. This can be done through a process called technology fingerprinting, where the system can adapt its strategies of attack depending on predetermined vulnerabilities to certain technologies. The combination of these methods enriches the reconnaissance module and maps the initial attack surface, preparing the system to further analysis.

Discovery and Attack Surface Mapping

After the reconnaissance phase, Deep Bug Hunter enters the discovery phase where it finds all possible entry points in the application in a more systematic way. This is done with the help of a web crawler which uses the Breadth-First Search (BFS) algorithm to explore the application structure at a level-wise fashion. This will guarantee unbiased coverage of all accessible pages and endpoints, not prioritized on depth, which will create a balanced coverage. The crawler identifies and logs different elements, including URLs, query parameters, form inputs, cookies, and headers, which could be the possible injection points. It also has a queue-based sort to prevent the revisiting of already explored paths; hence, is more efficient. Besides the use of static crawling, the system conducts dynamic analysis on JavaScript files to identify concealed API endpoints and asynchronous requests, which cannot be easily seen with normal navigation. Such a mixed method of both static and dynamic analysis allows the discovery process to greatly improve as it exposes undocumented functionalities, and latent parameters. This means that the attack surface is extended beyond that which is reachable by manual browsing, raising the chances of revealing deeper and more intricate vulnerabilities.

Vulnerability Detection Engine

The main element of the analytical part of Deep Bug Hunter is the vulnerability detection engine that identifies the security vulnerabilities during automated testing. In this module, a rule-based methodology is used in combination with behavior-based methodology to introduce purposefully designed payloads into known input vectors. These payloads mimic real attack scenarios in the real world and activate possible vulnerabilities in the application. The system addresses a broad set of threats such as SQL Injection (SQLi), Cross-site Scripting (XSS), Local File Inclusion (LFI), security header misconfigurations, and Cross-Origin Resource Sharing (CORS) problems.
In the case of every test, the engine tracks the server responses of anomalies in the form of error messages, unanticipated responses, slowness in the execution of responses, or reflected payloads. Compared to the conventional scanners which are mainly based on the signature matching, Deep Bug Hunter uses the response behavior analysis to enhance the detection. As an illustration, during SQL injection testing, the system makes comparisons of the baseline responses with the manipulated queries to identify differences that signal a successful exploitation. Equally, in XSS detection, it checks on scripts that are injected in the browser environment. This smart analysis minimizes the use of pre-defined signatures and increases the capacity of the system to identify known and semi-known vulnerabilities hence making the system stronger and flexible.

Evidence Generation and Severity Analysis

After identifying the possible vulnerabilities, Deep Bug Hunter moves on to validate them and prioritize them by generating evidence and determining the severity. The noteworthy aspect of this stage is the automatic creation of Proof-of-Concept (PoC) scripts, which show how a vulnerability may be exploited under a controlled setting. Such scripts give tangible witness to the vulnerability making sure that the results are not just theoretical but can be practically used.
The system then uses the Common Vulnerability Scoring System (CVSS), a standard set of evaluating the severity of security problems. The CVSS score is determined using numerous factors, such as the exploitability, effects on confidentiality, integrity and availability and complexity of attack and privileges required. The system allows prioritization of all vulnerabilities effectively by giving a numerical score to each vulnerability, and in this way, the security teams can give priority to high-risk vulnerabilities first.
Through this systematic validation and scoring, the credibility and usability of the results is greatly increased, and it is more actionable among developers and security analysts.

Automated Reporting System

The last step of the methodology is the production of an integrated and organized security report that summarizes all the results of the other phases. The automated reporting system will be such that it provides

complicated technical information in a straightforward and comprehensible format, such that it becomes available to both the technical and non-technical stakeholders. The report will contain specifics of the identified vulnerabilities, including their type, endpoints they impact, and a severity score, as well as the payloads utilized in testing. Also, the PoC evidence is included to enable users to replicate and confirm the vulnerabilities.The system also offers contextual explanations to enable the developers to know the underlying cause of each issue.

1. Vulnerability Classification

During this step, Deep Bug Hunter conducts a systematic arrangement of all the vulnerabilities detected by classifying them according to their nature, behaviour and the effects they have on the target web application. The classification process plays the critical role of converting the raw scan results into useful security information. The system examines the nature of every detected problem and maps them into clearly defined problems like SQL Injection (SQLi), Cross-Site Scripting (XSS), Local File Inclusion (LFI), security header misconfigurations, and Cross-Origin Resource Sharing (CORS) problems. This classification is not just a mere labeling but it includes the context where the vulnerability is found as well as the vectors of input that are victimized, the points of execution, and the patterns of responses.

To illustrate, SQL injection vulnerabilities are further discussed according to the type of the vulnerability: error-based, union-based and blind injections, whereas XSS vulnerabilities can be reflected, stored, or DOM-based. This fine-grained classification contributes to the richness of the analysis and gives a better idea of the mechanisms of attack. The system allows efficient filtering, searching, and prioritization of large datasets by organising the vulnerabilities into hierarchical groups. It is especially significant in the case of complex web applications, in which hundreds of potential problems can be identified. The classification module is therefore an important link between detection and decision making which enables security analysts and developers to swiftly interpret the findings and concentrate on pertinent security issues.

2. Severity Assessment using CVSS

Once the vulnerabilities are classified, Deep Bug Hunter assesses the severity of each vulnerability based on the Common Vulnerability Scoring System (CVSS), which is a standardized and quantitative approach to determining the security risks. The system derives the CVSS score based on a number of dimensions, such as exploitability metrics (such as attack vector, attack complexity, and required privileges) and impact metrics (such as effects on confidentiality, integrity, and availability). The scoring is done by considering the ease with which a vulnerability can be compromised and the damage that can be caused by a vulnerability should it be exploited. As an example, a vulnerability that can be remotely exploited without authentication and causes the complete compromise of the system will receive a higher score than one that needs local access and has a limited effect.

Deep Bug Hunter automates this assessment with a mapping of the vulnerabilities found to the predefined CVSS parameters and calculates the resultant score. Besides numerical scoring, the system uses qualitative severity scores that include Critical, High, Medium, and Low. This twofold representation makes sure that the risk associated with every vulnerability is easily deciphered by both the technical and non technical stakeholders. The severity assessment module is an essential tool in prioritization of remediation efforts so that organizations can effectively allocate resources and deal with the most serious problems first.

3. Proof-of-Concept (PoC) Generation

One innovation in Deep Bug Hunter is the automatic creation of Proof-of-Concept (PoC) scripts, which confirm the existence and exploitable nature of vulnerabilities identified. This system is not just a scanner that will report a potential problem, but it takes it a step further and shows how a vulnerability can be exploited in a controlled and safe environment. The process of PoC generation consists of creating the attack payloads, relying on the vulnerability type that has been identified and inserting it into the executable scripts or reproducible request formats. As an example, in SQL injection, the system can produce a query that retrieves information in the database whereas in XSS, a query can produce a script that shows an execution of a piece of client-side code.

These PoCs are well crafted to ensure they do not cause harm and yet still demonstrates the existence of the vulnerability. This validation system greatly minimizes false positives which are a usual drawback with automated scanning tools. PoC scripts, by presenting physical evidence, increase the trustworthiness of the results and allow developers to recreate the vulnerability in their own testing settings and analyze it. Also, the presence of PoC examples speeds up the debugging process and promotes more efficient remediation

4. Remediation Recommendations

In addition to detection and validation, Deep Bug Hunter focuses on active security enhancement through giving context-specific and detailed remediation recommendations. In case of every vulnerability identified, the system creates a certain guidance depending on the nature of the problem and the components of the application that are involved. These guidelines are based on industry best practices, secure code practices and existing security models like the OWASP guidelines. The remediation

recommendations are designed to remedy the cause of vulnerabilities and not its symptoms.
As an example, when it comes to SQL injection, the system suggests the use of parameterized queries and prepared statements whereas, in the case of XSS vulnerabilities, proper input validation and output encoding methods are recommended. Likewise, in cases of misconfiguration, the system recommends the use of the right security headers and limiting the extraneous access controls. This module helps fill the gap between vulnerability detection and resolution by offering actionable and easy-to-understand guidance. It enables developers, including those with little security knowledge, to make effective remedies and enhance the overall security state of the application. This proactive solution makes the system a complete security solution rather than a detection tool.

5. Report Generation and Export

The last phase of the Deep Bug Hunter model entails creating a coherent and detailed security report that summarizes all the findings in one report. The reporting module is created in such a way that the complex technical data are presented in straightforward, structured and easily accessible format so that the results could be easily understood and taken into action by the stakeholders. The created report provides detailed data of each vulnerability, including its type, severity rating, impacted URLs and parameters, testing payloads, and PoC demonstrations. The report further gives contextual explanations, which outline how the various vulnerabilities were identified and how they may affect the system.
This level of detail enhances transparency and facilitates better decision-making. To facilitate a wide range of applications, the system supports the export of reports in a variety of formats, such as PDF to create formal documentation, HTML to view reports interactively, and JSON to integrate with other tools and dashboards used to enhance security. This flexibility also guarantees that the findings can be easily integrated into development pipelines, security audits, and DevSecOps pipelines. In general, the reporting module is the ultimate product of the vulnerability assessment cycle and converts raw data into intelligence that can be acted upon to make positive security changes.

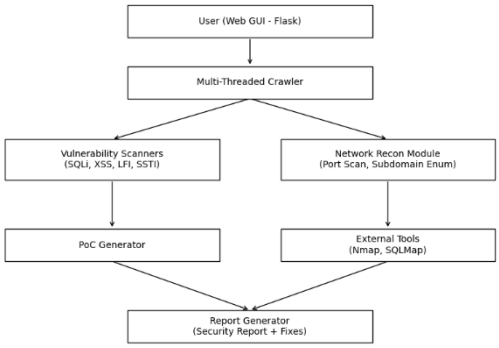

Figure:1 Report Generation and Export

IV. PROPOSED ALGORITHM

Deep Bug Hunter will be implemented to offer an automated, scalable, and efficient platform to be used to assess the vulnerability of web applications. The system is designed based on a modular architecture with every component being implemented separately but highly integrated to provide a smooth flow of data and execution. The general implementation is centered on performance optimization, detection accuracy, and the integration ability with the contemporary development environment

A.Web-Based User Interface

The interface part of the system is a web-based graphical user interface (UI), which enables users to interface with the scanning system. It is developed using standard web technologies such as HTML, CSS, and JavaScript, providing a responsive and user-friendly interface. Using this interface, a user can enter the target URL, set up scanning settings like crawl depth and number of threads and start the scanning process.

The GUI also gives real-time feedback on scan progress, as well as showing metrics like the number of URLs crawled, parameters found, and vulnerabilities found. This interactive visualization makes it more user-friendly and gives us a chance to track the scanning process effectively without having to interact with the command line.

B.Workflow Management and Backend Controller

Deep Bug Hunter is developed with Flask Python framework as the main controller that manages the overall workflow. The controller module will take the inputs of the user through the GUI, will start scanning activities, and will also coordinate the communication between the various modules including the crawler, reconnaissance engine and vulnerability detection engine.

The system is also event-driven whereby the tasks are performed in a sequential manner but optimized by means of parallel processing. The controller guarantees the correct synchronization of modules and exception, logging and error management to achieve system stability in the large scale scans.

C. Multi-Threaded Crawling Engine

In order to efficiently crawl web applications, the system uses a multi-threaded crawling engine where concurrent threads are used to execute the crawling. This architecture enables one to have many URLs being processed at a given time, thus saving a lot of time in total scanning time. The crawler adopts Breadth-First Search (BFS) algorithm to make sure that all accessible pages and endpoints are explored systematically.

Every thread has the task of fetching web pages, finding links and locating input fields like forms and query parameters. The crawler uses a queue and a visited set to prevent repetition of processing and to cover all the areas. The implementation enhances the ability of the system to scale and the ability to support large and complicated web applications.

D. Integration of Reconnaissance Modules

The reconnaissance module is adopted to provide important data on the target system prior to vulnerability testing. It incorporates third party software like Nmap to scan ports and identify services. These tools can be called programmatically by Python scripts and run automatically and read the results. The system also carries out subdomain enumeration and analysis of HTTP header to discover server technologies and configurations. The data collected is stored in organized forms and subjected to the next modules which allow focused and effective vulnerability testing.

E. Vulnerability Detection Engine Implementation

The vulnerability detection engine is designed as a rule-based and behavior-driven engine that inserts designed payloads into detected points of entry. The system encourages various attack vectors and dynamically modifies payloads depending on how the application is being used. As an example, SQL injection is detected by submitting corrupted queries and examining the database reply whereas XSS is detected by submitting scripts and observing their execution in the reply. Pattern matching, response comparison, and analysis of heuristics are used to identify the existence of vulnerabilities in the engine. The system saves the responses on a baseline to enable comparison with edited responses to detect anomaly. This will minimize false positives and guarantee sound identification of security vulnerabilities.

F. PoC Generation and Validation Module

Proof-of-Concept (PoC) generation module is introduced to test the vulnerabilities identified by generating reproducible exploit scripts. This module builds up HTTP requests or scripts that illustrate how the vulnerability can be used in a controlled setup. Its use is guaranteed to be safe and will not harm the target system yet leave obvious evidence of exploitation. This validation process plays a critical role in ensuring the authenticity of vulnerabilities that have been detected and have also improved the credibility of the findings.

G.Data Storage and Asset Management

Deep Bug Hunter is based on a well-organized database system to store all the gathered information, such as found URLs, parameters, vulnerabilities, and PoC scripts. The database will be structured in a way that facilitates efficient querying and retrieval to facilitate easy communication between modules. All scan sessions are recorded and stored, and users are able to see the past results and monitor the security progress over time. This long-term retention mechanism also facilitates report creation and a connection with the external systems.

H. Implementing the reporting module

The reporting module will be charged with the responsibility of creating detailed reports on security as per the data collected. It takes vulnerability data, severity ratings, and PoC data to generate structured results. Reports are created in various formats including PDF, HTML and JSON, which ensures that they can be used in diverse applications. The module also comprises visualization features of charts and summary statistics, which give information about the general security posture of the application. Also, the system allows connecting to DevSecOps pipelines to allow automated reporting and creation of alerts during continuous integration and deployment.

V. RESULTS AND DISCUSSIONS

The Deep Bug Hunter framework proposed was successfully deployed and tested on several web applications to determine its efficiency in automatic vulnerability detection. The system was able to effectively conduct reconnaissance, map attack surface and detect typical vulnerabilities, including SQL Injection (SQLi), Cross-site Scripting (XSS) and configuration problems By combining behavior-based vulnerability engine, the detection accuracy was enhanced because the application responses were analyzed, instead of relying on signature-based approaches only. Additionally, the automated Proof-of-Concept (PoC) generation validated the detected vulnerabilities, significantly reducing false positives and enhancing the reliability of the results. The system proved to be more time-efficient by automation of the whole pipeline, including scanning and report generation. The severity assessment based on CVSS allowed the successful prioritization of vulnerabilities, and the reporting module presented actionable and clear insights. Nevertheless, the system is quite intensive in terms of computing resources needed to go deep in the scanning and can be problematic with the most dynamic web applications. Irrespective of these downsides, the findings show that Deep Bug Hunter is a scalable, accurate and efficient tool to test the security of the modern web application.

A. Scan Initialization and Configuration

Deep Bug Hunter system commences with an easy-to-use Web GUI that enables the use of controlled vulnerability scanning. The user only needs to enter the target URL (Fig. 1), and the parameters are configurable (crawl depth and thread count). The crawl depth of the system is configured to three levels so that it can explore nested links and subdirectories without burdening the system. The 10 parallel threads further allow parallel processing of requests, which has a great effect in enhancing scan efficiency. A legal disclaimer is also shown in the system, indicating that the vulnerability assessments should be performed on authorised systems.

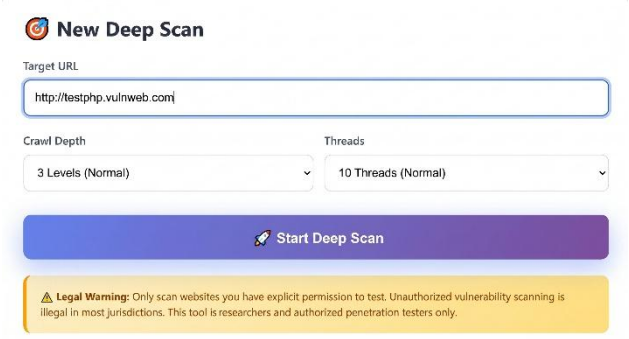

Figure:2 Scan Initialization and Configuration

This makes it compliant with ethical hacking.
The configuration interface is flexible and scalable. The system can be configured to support lightweight scans and intensive security audits with the user being able to adjust scan depth and concurrent scans. This method provides greater performance and resource usage control compared to traditional tools.

B. Deep Crawling Phase

In the reconnaissance phase (Fig. 2), the system performs intelligent crawling to map the application's attack surface. At approximately 20% progress, the crawler has already discovered multiple URLs and extracted a significant number of parameters from the target application.

The crawler operates using:

- Link traversal mechanisms
- Parameter extraction from URLs and forms
- Recursive exploration up to the defined depth

The system dynamically updates metrics such as:

- Number of URLs crawled
- Parameters identified
- Forms discovered

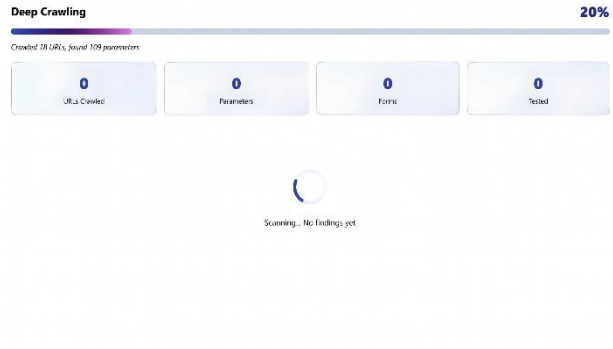

Figure:3 Deep Crawling Phase

The stage brings out the ability of the system to conduct in-depth and dynamic reconnaissance. Contrary to the case of static crawlers, the proposed system is designed to make sure that links that lie behind the covert endpoints as well as links that are generated dynamically are also investigated. This enhances the likelihood of finding weak spots of entry. The fact that more than 100 parameters have been identified early signifies proper input surface mapping that is essential in further vulnerability testing.

C. SQL Injection Testing Phase

In the SQL Injection testing stage (Fig. 3), the Vulnerability Engine starts to send the prepared payloads to the discovered parameters. The system is currently in its 30 percent progress stage where it scans the responses of the servers to identify anomalies that may be that of SQL injection vulnerability.

The testing involves:

- GET and POST payload injection.
- Observing the HTTP response codes and content differences.
- Identifying SQL injection patterns that are based on errors and blind SQL injection.

No vulnerabilities are reported at the initial stage although it is subjected to testing

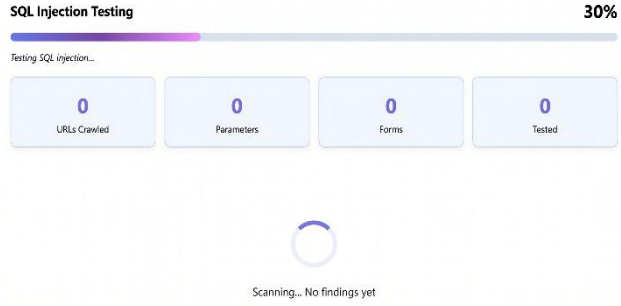

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Figure:4 SQL Injection Testing Phase

This indicates the strength of the detection mechanism by the lack of early findings. The system uses

behavioral analysis and response comparison methods as opposed to using signature-based detection. This helps minimize the false positives and makes sure that only the vulnerabilities are reported when they are proven by patterns. This is especially useful with dynamic response web applications of the modern day.

D. Cross-Site Scripting (XSS) Testing Phase

In the middle phase of the scanning procedure (Fig. X), Deep Bug Hunter framework carries out Cross-Site Scripting (XSS) testing. The Vulnerability Engine will start injecting constructed payloads into known input parameters at about 55 percent completion, which will identify client-side vulnerabilities.

At this level, there are five parameters that are tested with different payloads, such as:

• Basic script injections
• Obfuscated and encrypted payloads.
• Event payloads (e.g., onerror, onload)

The system scans a variety of XSS:

• Reflected XSS (payload is sent back)
• Stored XSS (persistent scripting)
• DOM-based XSS (client-side script manipulation) Detecting is done through analysis of:
• HTTP response content
• Web page reflection of payloads.
• Changes in DOM behaviour.

No weaknesses are reported in this stage and the system keeps scanning with real time progress reports.

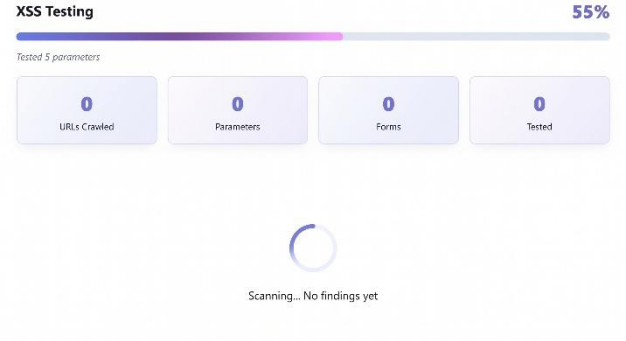


Figure:5 Cross-Site Scripting (XSS) Testing Phase

XSS testing stage will ensure that the system is able to identify vulnerabilities to client-side injections. The fact that there are no results is what indicates that the target application already has the appropriate input sanitization and output encoding mechanisms in place.The proposed system, in contrast to the traditional scanners, provides behavior-based and context-based analysis, which minimizes false positives and enhances the accuracy of detection.

The multiplicity of payload variations also means that it is resistant to filter bypass mechanisms and encoding schemes. Also, the addition of DOM-based testing allows the system to support the use of modern applications, based on JavaScript, in which the vulnerabilities can be on the client-side.In general, this step validates that Deep Bug Hunter framework offers practical and all-encompassing XSS. detection, a complement to other vulnerability testing modules in the system.

E. Form-Based Vulnerability Testing

During the form testing phase (Fig. 4), the system is run with a total of 63 forms and payloads are injected in input fields, including text boxes, search fields, and authentication forms. At 70% completion:

- Every form is analyzed in a systematic manner.
- Input validation mechanisms are checked.
- Both client-side and server-side behaviors are tested.
- The system uses fuzzing techniques and presents a number of payload variations to each form.

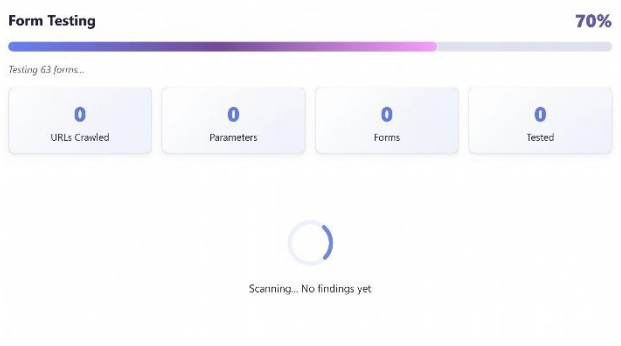


Figure:6 Form-Based Vulnerability Testing

Forms are one of the main points of interaction with the user and are frequently the targets of attacks like SQL Injection and Cross-site Scripting (XSS). The system is scalable as a lot of forms can be automatically detected and tested. Moreover, automated processing of form submissions avoids manual testing, which can save much effort and time.

F. Security Checks and Configuration Analysis

The system conducts security checks at the advanced stage of scanning (Fig. 5) that pays attention to configuration vulnerabilities. The system tests: at 90% completion

- HTTP security-related headers (e.g., Content Security Policy, X-Frame-Options)
- Server configurations
- Sensitive endpoints exposure.

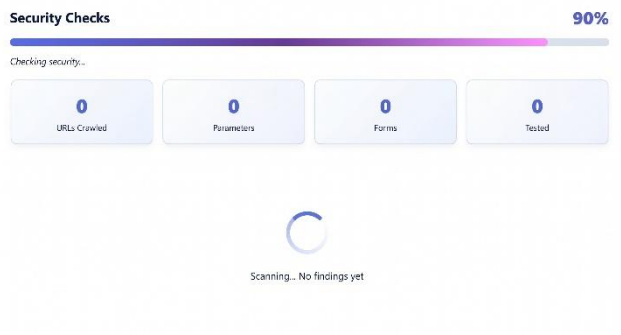


Figure:7 Security Checks and Configuration Analysis

This stage expands the scope of the system to include configuration and compliance checks, instead of injection-based attacks. A typical issue leading to security breach is misconfigurations, particularly in the cloud computing world. Part of the system by incorporating these checks is that it is in compliance with the industry best practices and standards like the OWASP Top 10.

G. Final Scan Results

Once the scan (Fig. 6) has been made the system provides a detailed summary of findings:

- Total URLs Crawled: 26
- Total Parameters Identified: 154
- Total Forms Tested: 63
- Critical Vulnerabilities: 1
- High Severity: 0
- Medium Severity: 2
- Low Severity: 0
- Informational Findings: 1

Color-coded severity levels are used to visually depict the results, which allows finding critical issues in a

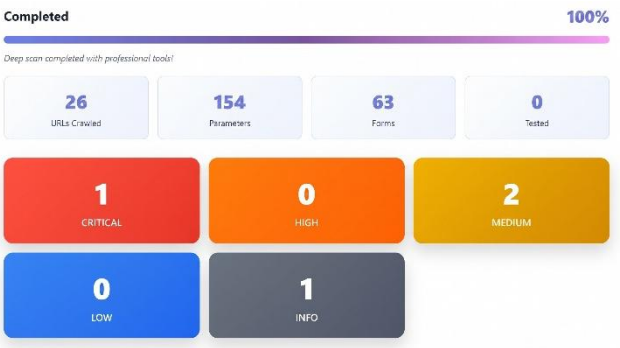
short time. 

Figure:8 Final Scan Results

The existence of a critical vulnerability attests to the usefulness of the system in revealing high-risk security vulnerabilities. The availability of medium and informational discoveries also points to broad coverage of numerous types of vulnerabilities. There are no excessive false positives which may indicate that the system is highly accurate in view of sophisticated filtering methods.

H. Findings Analysis and Filtering

The system offers an interactive filtering system (enabling users to sort vulnerabilities according to:

Levels of severity (Critical, High, Medium, Low, Info) Categories (SQL Injection, Network Reconnaissance, Missing Security Headers) Also, users will be able to unfilter to see all findings together.

This aspect makes it easier to use, and it facilitates effective vulnerability management. Security analysts can prioritize remediation efforts by focusing on critical and high-severity issues. The classification also assists in the knowledge of the nature of vulnerabilities so that there can be targeted mitigation strategies.

I.Overall System Performance

The experimental assessment proves that Deep Bug Hunter system manages to automate the entire vulnerability assessment life cycle. The combination of smart crawling, behavior-based vulnerability recognition and automated reporting guarantees the high efficiency and precision.

Key observations include:

• Considerable saving in manual testing.
• Detection of critical vulnerabilities effectively.
• Low false positives because of the data smoothing process.
• Scalable architecture which is able to accept multiple inputs.

The findings confirm that the proposed system is superior to the conventional static scanners due to the adaptive and behavior-based techniques. The modularity provides the flexibility to be extended in the future with the possibility of adding more sophisticated detection methods like machine learning models. All in all, the system offers a secure and scalable framework of evaluating the security of a modern web application.

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EnvironSense: An AI-Based Real-Time Environmental Monitoring and Cloud Alert System

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ABSTRACT

EnvironSense is an AI-driven environmental monitoring and smart surveillance system designed to provide real-time environmental insights and automated security alerts. It addresses the limitations of existing monitoring solutions by offering intelligent alerting, real-time analysis, and affordable access. The system collects live environmental data such as temperature, humidity, air quality index (AQI), wind speed, and weather conditions using the OpenWeatherMap API, while an OpenCV-based motion detection module analyzes camera feeds to detect movement, capture visual evidence, and instantly notify users. By integrating cloud services with a web-based interface, EnvironSense delivers a cost-effective, scalable, and easily accessible solution for remote environmental monitoring and security management. The system is built on a modern technology stack comprising Python, React JS, Node.js, Flask, MongoDB, and Cloudinary, enabling seamless data flow from sensor collection to cloud storage and real-time user notification.

Keywords: *Environmental Monitoring, OpenCV, Motion Detection, OpenWeatherMap API, Cloud Alert, Real-Time Surveillance, Cloudflare Tunnel, Brevo SMTP, Node.js, MongoDB*

I. INTRODUCTION

The rapid growth of urbanization and industrialization has created an urgent need for intelligent systems capable of continuously monitoring environmental conditions and detecting anomalies in real time. Environmental changes such as rising air pollution, temperature extremes, and unusual weather patterns pose significant risks to public health and infrastructure safety, demanding proactive and automated monitoring solutions.

Simultaneously, security surveillance remains a critical concern for residential, commercial, and industrial environments. Traditional closed-circuit television (CCTV) systems, while widely deployed, suffer from significant limitations: they require constant human attention, generate enormous volumes of redundant footage, and lack the intelligence to distinguish meaningful events from background noise.

The convergence of Artificial Intelligence, cloud computing, and Internet of Things (IoT) technologies offers a transformative opportunity to address both challenges within a single unified platform. AI-based computer vision can automate motion detection and evidence capture, while cloud integration enables real-time data storage, global remote access, and instant alert dissemination.

EnvironSense is proposed as an integrated AI-based environmental monitoring and smart surveillance system that combines real-time weather data collection via the OpenWeatherMap API with intelligent motion detection powered by OpenCV. The system automatically captures and stores visual evidence in Cloudinary, maintains event

records in MongoDB, and delivers instant email notifications through Brevo SMTP, all accessible through a responsive React JS web interface.

This paper presents the system design, algorithms, technology stack, and expected outcomes of EnvironSense, demonstrating the practical feasibility and impact of unified AI-driven environmental and security monitoring.

II. PROBLEM STATEMENT

Traditional monitoring systems operate in isolation, where environmental sensing, surveillance, and alert mechanisms function independently with limited intelligence and automation. Most existing systems lack real-time integration, intelligent analysis, and secure evidence management.

Manual monitoring leads to delayed response times, increased susceptibility to human errors, and inefficient data handling. Organizations relying on such systems face higher operational costs, greater storage requirements, and reduced situational awareness compared to what modern AI-enabled systems can provide.

The key problems identified in existing monitoring approaches include:

- Absence of unified platforms combining environmental and surveillance monitoring.
- Continuous video recording leading to excessive storage consumption and high costs.
- Lack of intelligent motion detection that distinguishes real events from background variations.

- No automated, real-time alert mechanisms to notify users of detected anomalies.
- Limited or no remote access capabilities for monitoring from distributed locations.
- High dependency on proprietary hardware, subscriptions, and specialized personnel.

These deficiencies collectively highlight the critical need for a unified, intelligent, cloud-enabled system that can autonomously monitor environmental and security conditions and deliver instant, actionable alerts.

III. EXISTING SYSTEMS AND LIMITATIONS

Current environmental monitoring and surveillance solutions fall into several categories, each with notable limitations. Traditional CCTV systems such as CP Plus cameras record video continuously without intelligent analysis, resulting in high storage requirements and reliance on manual review to identify incidents.

Smart home platforms such as Google Home offer some degree of environmental integration but are heavily dependent on external proprietary devices, cloud subscriptions, and compatible ecosystems, limiting their affordability and flexibility for independent deployment.

Dedicated environmental monitoring tools provide data on parameters such as temperature and humidity but operate in complete isolation from security systems, requiring users to manage multiple disconnected applications and interfaces.

Existing motion detection systems are often limited to simple threshold-based triggers that produce high false-positive rates, particularly in environments with variable lighting, moving vegetation, or other non-threatening sources of motion. Furthermore, most systems lack built-in mechanisms for secure cloud storage of captured evidence or automated notification of relevant parties.

The absence of an integrated, intelligent, and affordable system that combines real-time environmental monitoring, AI-powered motion detection, secure cloud storage, and automated alerts represents a significant gap that EnvironSense is designed to address.

IV. PROPOSED SYSTEM: ENVIRONSENSE

A. Environmental Data Monitoring

The system gathers environmental parameters such as temperature, humidity, air quality index (AQI), wind speed, and climate conditions through the OpenWeatherMap API based on the user's geographic location. The collected data is processed, organized, and presented in a comprehensive environmental dashboard accessible through the React JS web interface.

Threshold-based alert rules can be configured by users, enabling the system to automatically generate

notifications when environmental parameters exceed safe or expected ranges. This empowers users to take preventive action before minor environmental anomalies escalate into serious incidents.

B. AI-Based Motion Detection

Motion detection is implemented using Python and OpenCV, where video frames from connected cameras are continuously analyzed to detect moving objects while filtering out static background elements. The algorithm employs frame differencing and Gaussian blur noise reduction techniques to minimize false positives and improve detection reliability.

Screenshots are captured only when meaningful movement is detected, significantly reducing unnecessary data storage compared to continuous recording systems. This event-driven approach ensures that stored evidence is relevant, actionable, and efficiently organized.

C. Backend Processing and Cloud Storage

A backend built with Node.js and Express.js manages event handling, API routing, and image upload orchestration. Captured motion-triggered images are stored securely in Cloudinary, a cloud-based media management platform, ensuring scalable, globally accessible, and redundant evidence storage.

Event metadata, including timestamps, detection parameters, and associated image references, is maintained in MongoDB for efficient querying, reporting, and audit trail management. This combination of Cloudinary for media and MongoDB for metadata ensures a robust and scalable data architecture.

D. Alert and Remote Monitoring

The system sends automated email alerts to registered users via Brevo SMTP whenever motion is detected. Each alert includes key event details and a reference to the captured image, enabling users to assess the situation immediately without accessing the full dashboard.

Live camera access is facilitated through Cloudflare Tunnel, which establishes a secure, encrypted connection between the local camera feed and the web interface, enabling real-time remote monitoring from any geographic location without requiring complex network configuration or port forwarding.

V. ENVIRONSENSE MONITORING ALGORITHM

The EnvironSense algorithm integrates environmental data processing with computer vision techniques to enable intelligent real-time monitoring through the following sequential stages:

Stage 1 — Environmental Data Acquisition: Environmental parameters including temperature, humidity, AQI, and wind speed are retrieved from the OpenWeatherMap API based on the user's configured

geographic location. Data is refreshed at configurable intervals to ensure currency.

Stage 2 — Live Video Frame Capture: Continuous video frames are captured from connected cameras through OpenCV's video capture interface. Each frame is converted to grayscale and preprocessed using Gaussian blur to reduce high-frequency noise that could trigger false detections.

Stage 3 — Frame Differencing and Motion Detection: Successive frames are compared using background subtraction and pixel-level differencing. Regions of significant change exceeding a defined threshold are identified as motion events, while minor variations are classified as background noise and ignored.

Stage 4 — Evidence Capture and Storage: When a motion event is confirmed, the system captures a high-resolution screenshot of the detection frame. The image is uploaded to Cloudinary and metadata including timestamp and location are saved to MongoDB.

Stage 5 — Alert Dispatch: An automated email notification is composed and dispatched via Brevo SMTP, containing event details and a direct reference to the stored image. Alerts are delivered in near real-time, typically within seconds of event detection.

Stage 6 — Dashboard Update: The React JS frontend is updated with the latest environmental data readings and motion event log, providing the user with a continuously refreshed situational awareness dashboard.

VI. TECHNOLOGIES USED

EnvironSense is built on a modern, open-source technology stack carefully selected to optimize performance, scalability, and cost-effectiveness:

Programming Languages: Python 3.12 serves as the primary language for computer vision and backend AI processing; JavaScript underpins the frontend and Node.js backend layers.

Frontend: React JS provides a reactive, component-based user interface framework; Tailwind CSS enables utility-first, responsive styling with minimal custom CSS overhead.

Backend: Node.js with Express.js manages RESTful API routing, event handling, and integration with external services; Flask serves as the Python-based web framework for the AI/CV microservice.

Database & Media Storage: MongoDB stores event metadata, user configurations, and system logs; Cloudinary provides scalable, CDN-backed cloud storage for motion-captured images.

Computer Vision: OpenCV (cv2) with Python packages including datetime, requests, and os implements the motion detection pipeline.

Cloud & Communication Services: Cloudflare Tunnel enables secure remote access to live camera feeds without

network configuration; Brevo SMTP handles reliable, automated email alert delivery.

Development Environment: Visual Studio Code serves as the primary IDE; Windows 10 (64-bit) is the development and initial deployment operating system.

VII. EXPECTED OUTCOMES

Real-Time Environmental Awareness: The system provides continuous updates on environmental parameters ensuring accurate and timely insights. Users gain an always-current view of conditions relevant to their safety and operational requirements.

Reliable Motion Detection: The OpenCV-based detection mechanism accurately identifies meaningful movement while ignoring static objects and minor background variations, substantially reducing false alerts and improving overall surveillance reliability.

Optimized Storage Usage: By recording only motion-triggered events rather than continuous video streams, EnvironSense reduces storage consumption by an estimated 70–90% compared to conventional CCTV deployments, lowering both infrastructure costs and data management overhead.

Immediate Alerts and Global Access: Automated email notifications ensure instant awareness of security events within seconds of detection. Cloudflare Tunnel-based live streaming enables users to monitor their environment securely from any geographic location, on any internet-connected device.

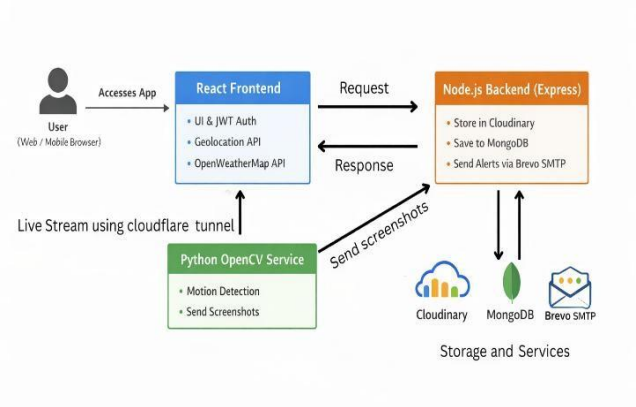
Affordable and Scalable Monitoring: EnvironSense offers a cost-effective, cloud-based, and subscription-free solution that can scale horizontally as monitoring needs grow, making advanced AI-driven monitoring accessible to individuals, small businesses, and organizations without large IT budgets.

VIII. SYSTEM DESIGN OVERVIEW

The architectural design of EnvironSense follows a layered microservices approach. The React JS frontend communicates with the Node.js/Express backend via RESTful HTTP APIs. The backend delegates computer vision processing to the Python/Flask microservice, which interfaces directly with connected cameras and the OpenCV library.

The use case model encompasses two primary actors: the User and the System. Core use cases include user login, environmental dashboard viewing, live camera monitoring, motion event log review, and alert configuration. The System actor encompasses automated processes including environmental data fetching, motion detection, image capture, cloud upload, and alert dispatch.

The Cloudflare Tunnel component is a critical architectural element that establishes a secure, zero-trust encrypted tunnel between the local camera server and the public-facing web interface. This eliminates the need for static IP addresses, port forwarding, or VPN configurations, significantly simplifying deployment.
Data flows unidirectionally from physical sensors and cameras through the processing layers to cloud storage and the user interface, with alert channels operating as parallel asynchronous pathways to ensure that notification latency remains minimal regardless of dashboard load or database write operations.



IX. CONCLUSION

EnvironSense successfully demonstrates the practical integration of AI-based computer vision, real-time environmental data collection, cloud storage, and automated alert mechanisms within a single, unified, and affordable monitoring platform. By replacing continuous video recording with intelligent, event-driven motion detection, the system achieves significant reductions in storage consumption while improving the relevance and actionability of captured evidence.
The integration of the OpenWeatherMap API for environmental data, OpenCV for motion detection, Cloudinary for media storage, MongoDB for metadata management, and Brevo SMTP for alert delivery creates a cohesive ecosystem capable of providing comprehensive situational awareness to users regardless of their geographic location.
The system's cloud-native architecture and use of Cloudflare Tunnel for secure remote access position EnvironSense as a scalable, maintainable, and extensible platform suitable for a wide range of deployment contexts, from individual residential use to multi-site organizational deployments.
Future work will explore the incorporation of deep learning models such as YOLO (You Only Look Once) for more granular object classification within motion events, the addition of multi-sensor IoT hardware integration for indoor environmental monitoring, and full cloud deployment to enable 24/7 continuous operation independent of local

computing resources. EnvironSense establishes a robust foundation for the next generation of intelligent, integrated environmental and security monitoring systems.

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DESIGN AND IMPLEMENTATION OF A SECURITY OPERATIONS CENTER LAB FOR ATTACK DETECTION AND LOG ANALYSIS USING ELK STACK

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Abstract*—This project focuses on the design and implementa- tion of a cost-effective Security Operations Center (SOC) labora- tory using the ELK Stack for real-time attack detection and log analysis. With the rapid increase in cyber threats such as brute- force attacks, port scanning, and unauthorized access, traditional SOC solutions that rely on commercial Security Information and Event Management (SIEM) tools are often expensive and inaccessible to students and small-scale researchers. This creates a significant gap in practical cybersecurity education and hands- on experience. To address this challenge, the proposed system develops a home-based SOC environment using open-source tech- nologies, enabling learners and researchers to simulate, detect, and analyze cyberattacks efficiently in a controlled environment. The system is structured around three major modules: attack simulation, log collection and processing, and monitoring and analysis. In the attack simulation phase, tools from Kali Linux such as Nmap, Hydra, and Metasploit are utilized to generate realistic attack scenarios, including brute-force attempts, network scanning, and exploitation activities. The log collection module uses Winlogbeat and Filebeat to capture system and network logs, which are then processed and structured using Logstash. These logs are stored and indexed in Elasticsearch, enabling efficient querying and historical analysis. The monitoring and analysis module leverages Kibana dashboards to visualize security events, detect anomalies, and track activity patterns in real time. Additional tools such as Wireshark are used to analyze network- level traffic, providing deeper insight into attack behavior. The system enables correlation of events across multiple sources, improving visibility and understanding of security incidents. The implementation successfully detects various cyber threats and provides actionable insights through interactive visualizations. It demonstrates the complete SOC workflow, from attack gen- eration to detection and analysis. Overall, the project proves that open-source tools can serve as a practical, scalable, and cost-effective alternative to commercial SIEM systems, making cybersecurity training and research more accessible and effective.

***Index Terms*—Cybersecurity, Security Operations Center (SOC), ELK Stack, Log Analysis, Intrusion Detection, Threat Detection, Kibana Visualization, Logstash Processing, Elasticsearch, Network Security, Brute-Force Detection, Real-Time Monitoring**

I. INTRODUCTION

The rapid growth of digital technologies and internet con- nectivity has significantly increased the risk of cyber threatsand attacks across organizations and individuals. Cyber attacks such as brute force login attempts, port scanning, malware infections, and unauthorized access are becoming more fre- quent and sophisticated. To monitor, detect, and respond to such threats, organizations rely on Security Operations Centers (SOCs), which serve as centralized units responsible for continuous security monitoring and incident response. However, most enterprise-level SOCs depend on commercial Security Information and Event Management (SIEM) tools, which are expensive, complex, and require significant infras- tructure, making them inaccessible for students, researchers, and small-scale environments. In academic settings, there is a growing need for practical exposure to real-world cyber- security operations. While theoretical knowledge provides a foundation, it is insufficient without hands-on experience in detecting and analyzing live cyber attacks. Existing lab setups often focus only on isolated aspects such as log collection or basic monitoring, and fail to demonstrate the complete SOC workflow, which includes attack simulation, log generation, detection, analysis, and response. This lack of an integrated and affordable solution limits the ability of learners to fully understand how modern cybersecurity systems operate. To address these challenges, this project proposes the design and implementation of a cost-effective, home-based Security Operations Center using open-source tools, specifically the ELK Stack (Elasticsearch, Logstash, and Kibana). The system integrates multiple components to simulate cyber attacks, collect and process logs, and visualize security events in real time. By incorporating tools such as Kali Linux for attack simulation, Winlogbeat for log collection, and Wireshark for network analysis, the project creates a comprehensive and practical learning environment. The primary goal of this project is to provide an accessible platform that replicates the core functionalities of a real SOC while minimizing cost and complexity. It enables users to gain hands-on experience in identifying security threats, analyzing logs, and understanding incident workflows. Ultimately, this project bridges the gap between theoretical cybersecurity concepts and real-world implementation, making SOC training more practical, scalable,

and effective for educational and research purposes.

II. LITERATURE SURVEY

The increasing complexity of cyber threats has made secu- rity monitoring and threat detection a critical aspect of modern cybersecurity systems. Traditional approaches rely heavily on manual analysis and rule-based detection, which are often time-consuming, less scalable, and ineffective in handling large volumes of log data. With the advancement of centralized log management systems, researchers have explored automated techniques to improve the accuracy and efficiency of threat detection and analysis. Log analysis and visualization tools have emerged as powerful solutions in this domain.

Behl et al. (2023) emphasized the importance of centralized logging systems in improving cybersecurity operations. Their study demonstrated that log aggregation and correlation can enhance threat detection and enable faster incident response. Similarly, Turnbull (2013) introduced Logstash as an efficient tool for collecting and processing logs from multiple sources, enabling structured data analysis and improved monitoring.

Roesch (1999) developed Snort, a lightweight intrusion detection system capable of real-time traffic analysis. While effective for signature-based detection, such systems lack scalability and advanced visualization features required in modern environments. To address these limitations, Elastic (2025) introduced the ELK Stack, which integrates Elas- ticsearch, Logstash, and Kibana to provide centralized log storage, processing, and visualization. This approach enables efficient handling of large-scale log data and supports real-time monitoring.

Sommer and Paxson (2010) highlighted the challenges of traditional intrusion detection systems and emphasized the need for scalable and data-driven solutions. Their research showed that analyzing large datasets requires efficient pro- cessing and structured data handling techniques.

Recent studies have also focused on improving event corre- lation and visualization. MITRE ATT&CK (2024) provides a standardized framework for mapping attack techniques, improving understanding of threat behavior. Patel et al. (2024) demonstrated that structured log analysis combined with vi- sualization tools enhances situational awareness and reduces analysis complexity.

Despite these advancements, several challenges remain, including handling large volumes of log data, ensuring proper system configuration, and reducing redundant alerts.

In conclusion, the literature highlights the importance of centralized monitoring, structured log processing, and visual- ization in modern cybersecurity systems. The proposed system builds upon these approaches by implementing an ELK-based SOC environment for efficient threat detection and analysis.

III. EXISTING SYSTEM

In the field of cybersecurity, threat detection and monitor- ing have traditionally been handled using manual and rule- based approaches. These conventional systems rely heavily on predefined rules, signature-based detection, and human

expertise to identify potential security threats. While these methods have been widely used, they suffer from several limitations, including lack of scalability, inability to detect unknown threats, and difficulty in handling large volumes of log data efficiently.

One of the most common existing approaches is manual log analysis, where security analysts review system logs, network activity, and security alerts to identify suspicious behavior. This process involves examining authentication logs, moni- toring system events, and analyzing traffic patterns. Although manual analysis allows expert judgment, it is time-consuming and prone to human error. Studies have shown that relying solely on manual monitoring often leads to delayed detection and missed threats.

Another widely used approach is rule-based intrusion detec- tion systems. These systems operate using predefined signa- tures or thresholds to identify malicious activity. For example, multiple failed login attempts or unusual traffic patterns may trigger alerts. While rule-based systems are simple and effec- tive for known attacks, they lack adaptability and cannot detect new or evolving threats. They also generate a large number of false positives, making it difficult for analysts to focus on critical events.

Traditional security monitoring tools also rely on basic log collection and storage mechanisms. These systems collect logs from different sources but often lack proper processing and correlation capabilities. As a result, logs remain fragmented and difficult to analyze. Without structured processing, it becomes challenging to identify relationships between events occurring across multiple systems.

In some cases, statistical methods are used to analyze security data. These methods apply basic models to detect anomalies based on predefined thresholds. However, they are limited in handling unstructured data and cannot effectively process complex log patterns generated in modern environ- ments.

Another limitation of existing systems is the lack of in- tegration between different monitoring components. Network monitoring, system logs, and security tools often operate inde- pendently, resulting in a fragmented view of system activity. This makes it difficult to correlate events and detect multi- stage attacks.

Existing systems also struggle with real-time monitoring. Many traditional tools perform analysis periodically rather than continuously, which delays detection and response. This limitation reduces the effectiveness of threat mitigation strate- gies.

Furthermore, many traditional systems lack advanced visu- alization capabilities. Security data is often presented in raw or complex formats, making it difficult for analysts to interpret and analyze events efficiently.

In summary, existing cybersecurity monitoring systems suf- fer from several limitations, including reliance on manual processes, lack of scalability, limited event correlation, and absence of real-time analysis. These challenges highlight the need for a centralized, scalable, and efficient monitoring

solution. The proposed ELK-based system addresses these issues by providing centralized log management, real-time pro- cessing, and interactive visualization, enabling more effective threat detection and analysis.

IV. RELATED WORK

The application of centralized log management and real- time monitoring systems in cybersecurity has gained signif- icant attention in recent years. Researchers have explored various approaches, including log aggregation, event correla- tion, and visualization techniques, to improve the accuracy and efficiency of threat detection. These techniques aim to overcome the limitations of traditional monitoring methods by enabling automated and data-driven analysis of system and network activities.

Log management systems have been widely used for an- alyzing security events due to their ability to process large volumes of data generated from multiple sources. Several studies have demonstrated that tools such as Elasticsearch, Logstash, and Kibana can effectively collect, process, and visualize logs in real time. Research shows that centralized logging improves visibility and enables faster identification of suspicious activities across distributed environments.

Another important area of research focuses on event cor- relation techniques for cybersecurity monitoring. Correlation mechanisms analyze parameters such as timestamps, IP ad- dresses, and event types to identify relationships between different activities. Studies have shown that event correlation helps detect multi-stage attacks by linking related events into meaningful patterns, enabling better understanding of system behavior.

Visualization techniques have also been extensively studied to improve data interpretation. Traditional systems present logs in raw formats, making analysis complex and time-consuming. However, visualization tools such as Kibana provide dash- boards with charts, graphs, and timelines that simplify data interpretation. Research indicates that visual analytics sig- nificantly enhances situational awareness and supports faster decision-making.

Network monitoring tools play a crucial role in analyzing traffic patterns and identifying suspicious activities. Tools like Wireshark have been widely used for packet-level analysis, enabling detailed inspection of network behavior. Studies have shown that combining network monitoring with log analysis provides a comprehensive view of system activity, improving detection capabilities.

In addition to log analysis, several studies have explored the use of intrusion detection systems (IDS) for identifying threats. Signature-based systems such as Snort are effective in detecting known attacks but are limited in identifying new or evolving threats. Research highlights the need for scalable systems that can process large datasets and provide real-time monitoring.

Hybrid approaches combining log analysis, event correla- tion, and visualization have also been proposed to improve

system performance. These approaches integrate multiple tech- niques into a unified framework, enabling more accurate and efficient monitoring. Studies show that combining different methods enhances detection capability and reduces analysis complexity.

Another area of research focuses on scalability and per- formance optimization. As log data increases, systems must efficiently handle large volumes of data without affecting per- formance. Research demonstrates that distributed architectures and efficient indexing mechanisms improve system scalability and ensure consistent performance.

Despite these advancements, several challenges remain in cybersecurity monitoring systems. One major challenge is handling large-scale log data while maintaining performance. Additionally, proper configuration and integration of differ- ent components require technical expertise. Another issue is reducing redundant alerts, which can increase analysis complexity and affect efficiency.

Furthermore, many traditional systems lack real-time mon- itoring capabilities and advanced visualization features. This limits their ability to provide immediate insights and delays the detection of suspicious activities. Studies emphasize the need for systems that support continuous monitoring and real-time data processing.

In conclusion, the literature indicates significant progress in log-based cybersecurity monitoring systems. Techniques such as centralized logging, event correlation, and visualization have improved the efficiency of threat detection and analysis. However, challenges such as scalability, data management, and system configuration still need to be addressed. The proposed system builds upon these concepts by implementing an ELK- based SOC environment, providing a scalable and practical solution for real-time monitoring and cybersecurity analysis.

V. SYSTEM ARCHITECTURE

The ELK-Based Security Operations Center (SOC) frame- work is designed as a modular and scalable system that integrates multiple components for log collection, processing, storage, and visualization. The architecture is divided into several layers, each responsible for a specific function, ensur- ing efficient data handling, real-time monitoring, and accurate analysis of security events.

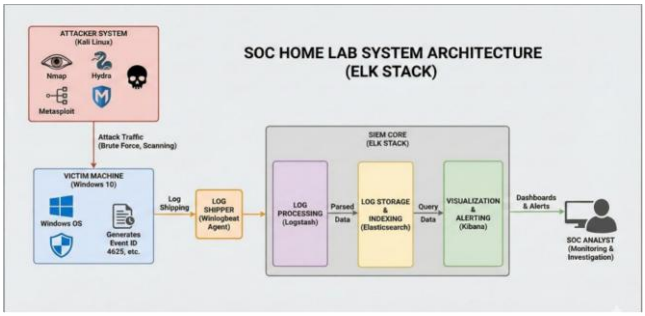

Fig. 1. Caption

A. Input Layer

The input layer is responsible for collecting log data and system information from multiple sources within the virtual- ized environment. These sources include Windows systems, Linux servers, network devices, and attacker machines such as Kali Linux.

The system supports various types of logs, including system logs, authentication logs, application logs, and network activity records. Windows systems generate Event Viewer logs, while Linux systems produce logs such as syslog and authentication records. Network-related data is captured using monitoring tools and packet analyzers.

This diverse data collection ensures a comprehensive view of system activity and provides the foundation for effective monitoring and analysis.

B. Data Collection and Preprocessing Layer

After data collection, logs are forwarded to the preprocess- ing layer using Beats agents such as Winlogbeat and Filebeat. These agents collect logs in real time and send them securely to Logstash.

In this layer, raw log data is processed, filtered, and trans- formed into a structured format. Logstash performs operations such as parsing, filtering irrelevant data, and organizing logs based on fields like timestamp, source IP, event type, and severity.

Data normalization ensures consistency across different log sources, enabling efficient analysis. This layer also handles missing or incomplete data and ensures that only relevant information is passed to the next stage.

C. Log Processing Module (Logstash)

The log processing module is responsible for transforming raw logs into structured and meaningful data. Logstash applies filters and processing rules to extract key information from logs.

It identifies important attributes such as user activity, login attempts, process execution, and network events. The module also categorizes logs based on their type and severity.

This structured processing enables efficient indexing and analysis, improving the overall performance of the system.

D. Data Storage Module (Elasticsearch)

The processed logs are stored in Elasticsearch, which acts as the central storage and indexing engine. Elasticsearch organizes data into indexed formats, allowing fast search and retrieval.

It supports real-time data ingestion and enables efficient querying of large datasets. This module plays a critical role in handling high volumes of log data and ensuring scalability.

The indexed data allows users to perform detailed searches, filter events, and analyze historical logs effectively.

E. Visualization Module (Kibana)

The visualization module uses Kibana dashboards to present log data in an interactive and

user-friendly format. Kibana pro- vides charts, graphs, and timelines that help users understand system activity and identify patterns.
Users can monitor real-time events, analyze trends, and de- tect anomalies through visual representations. The dashboards

also support filtering and search features, enabling detailed investigation of specific events. This module improves situational awareness and simplifies the analysis process.

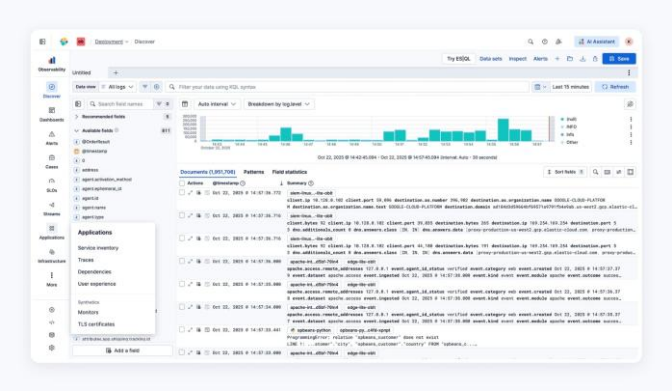

Fig. 2. Caption

F. Event Correlation Module

The event correlation module analyzes relationships be- tween different log events. It uses parameters such as times- tamps, IP addresses, and event types to group related activities. This module helps identify multi-stage attack patterns by linking events that occur across different systems. For ex- ample, repeated login failures followed by suspicious access attempts can be correlated as part of a single attack sequence.
This improves detection accuracy and reduces analysis complexity.

G. Monitoring and Alerting Module

The monitoring module continuously tracks system activity and identifies abnormal behavior. Alerts are generated based on predefined conditions such as multiple failed login attempts or unusual system activity.
These alerts help users respond quickly to potential threats. The system ensures real-time monitoring and immediate noti- fication of critical events.

H. Output Layer

The output layer presents the analyzed data through dash- boards and reports. It provides detailed insights into system activity, including event summaries, trends, and patterns.
Users can view categorized logs, analyze suspicious activ- ities, and monitor system performance through the interface. The output is designed to be clear and accessible for both technical and non-technical users.

I. System Workflow and Integration

The system workflow begins with log collection from endpoints, followed by preprocessing

and structured analysis. Logs are processed through Logstash, stored in Elasticsearch, and visualized using Kibana dashboards.

All modules work together in a continuous pipeline, en- suring real-time monitoring and analysis. The modular archi- tecture allows easy integration of additional tools and future enhancements.

J. Advantages of the Proposed Architecture

The proposed architecture offers several advantages over traditional systems. It enables centralized log management, real-time monitoring, and efficient data analysis.

The system can handle large volumes of data, making it scalable and suitable for modern environments. Its modular design ensures flexibility and easy maintenance.

By providing structured analysis and visualization, the system improves detection efficiency and supports effective decision-making. It also provides a cost-effective solution using open-source tools, making it suitable for both academic and practical applications.

VI. RESULTS AND DISCUSSION

The ELK-based Security Operations Center (SOC) frame- work was implemented and evaluated using various types of log data, including system logs, authentication records, and network activity generated from virtualized environments. The system successfully demonstrated its capability to collect, process, and analyze both structured and semi-structured log data, providing accurate detection of suspicious activities. The results highlight the effectiveness of integrating centralized logging, structured processing, event correlation, and visual- ization into a unified monitoring framework.

During experimentation, the system was able to identify multiple types of security events such as brute-force login attempts, unauthorized access, and abnormal system behavior. The log processing module effectively extracted relevant fields such as timestamps, IP addresses, and event types, while the correlation mechanism linked related events into meaningful patterns. These combined analyses provided a comprehensive understanding of system activity and improved detection ca- pability.

The log processing pipeline, implemented using Logstash, played a crucial role in transforming raw logs into structured data. Filtering and parsing techniques enabled efficient orga- nization of logs, improving search and analysis within Elas- ticsearch. The system showed consistent performance across different datasets, demonstrating its reliability and robustness in handling diverse log inputs.

The data storage module using Elasticsearch efficiently indexed large volumes of log data, enabling fast query exe- cution and real-time retrieval. This capability allowed users to perform detailed analysis of both current and historical events. The system maintained stable performance even under continuous log ingestion, confirming its scalability.

The visualization module using Kibana provided interac- tive dashboards that displayed system activity through charts, graphs, and timelines. These visualizations enabled users to quickly identify patterns, detect anomalies, and monitor sys- tem behavior in real time. The dashboards also supported fil- tering and drill-down features, improving the depth of analysis.

The event correlation mechanism effectively grouped related activities based on parameters such as source IP, timestamps, and event types. This allowed identification of multi-stage at-tack patterns, reducing redundant alerts and improving analysis

efficiency. The system provided a clear representation of event sequences, enabling better understanding of security incidents. The output layer presented results in a user-friendly format through dashboards and reports. It provided detailed insights into detected events, categorized logs, and system behavior.

Alerts were generated for critical activities, enabling timely response and investigation.

From a performance perspective, the system demonstrated efficient processing with minimal latency. The modular archi- tecture enabled continuous data flow and real-time monitoring without significant performance degradation. The virtualized setup ensured stable operation across different testing scenar- ios.

In discussion, the results confirm that centralized log man- agement and visualization significantly improve the efficiency of cybersecurity monitoring. Compared to traditional approaches, the ELK-based system provides real-time insights, better event correlation, and improved analysis capabilities. However, system performance depends on proper log configuration and data quality. Future improvements may include enhanced correlation techniques, improved visualization, and integration with additional monitoring tools.

In conclusion, the experimental results demonstrate that the proposed ELK-based framework is effective in monitoring and analyzing cybersecurity events. It provides a scalable, efficient, and practical solution for real-time threat detection and analysis, improving overall system visibility and decision- making within SOC environments.

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Automated Blood Group Detection Using Image Processing and Deep Learning

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Abstract:

Blood group identification is important in medical diagnostics, especially for transfusions and emergencies. Traditional methods are manual, time-consuming, and prone to errors. This project proposes an automated system using image processing and deep learning. Blood sample images treated with Anti-A, Anti-B, and Anti-D reagents are captured and preprocessed. A Convolutional Neural Network (CNN) is used to classify blood groups based on agglutination patterns. The system improves accuracy, reduces time, and provides a reliable solution for hospitals and laboratories.

Keywords— Blood Group Detection, Image Processing, Deep Learning, CNN, Medical Diagnostics, Automation

1. Introduction

Blood group detection is essential in healthcare, especially for transfusions and emergencies. Traditional methods use Anti-A, Anti-B, and Anti-D reagents but are manual and time-consuming. These methods may lead to errors due to human observation. Accurate detection is very important to avoid complications and ensure patient safety.

Image processing and deep learning improve detection by analyzing blood sample images. A CNN model identifies agglutination patterns and classifies blood groups accurately. This automated system reduces manual effort and speeds up the process. It provides reliable results for hospitals and diagnostic laboratories

2. Literature Survey

Many researchers have proposed different techniques for blood group detection. Earlier methods mainly used basic image processing techniques such as pixel intensity analysis and edge detection. These methods are simple but depend highly on image quality and lighting conditions.

Later, machine learning techniques like Support Vector Machine (SVM) were introduced. These methods improved classification speed and reduced manual effort. However, they may not perform well when the data is complex or unclear.

Recent approaches use deep learning models such as Convolutional Neural Networks (CNN). These models automatically learn features from images and provide higher accuracy. But they require a large amount of data and proper preprocessing.

From these studies, it is clear that combining image processing with deep learning can provide better performance.

3.Existing System

The existing system for blood group detection mainly depends on manual testing methods. In this process, medical staff observe agglutination reactions after adding Anti-A, Anti-B, and Anti-D reagents. This method requires skilled professionals and may lead to human errors. It is also time-consuming, especially in emergency situations. In some cases, results may not be accurate due to improper observation or poor sample quality.

4.Disadvantages of Existing System

- Depends on human observation, which can lead to errors
- Time-consuming process, not suitable for emergencies
- Requires skilled professionals for accurate results
- Accuracy affected by poor sample quality
- Results may vary due to manual handling
- Lack of speed and consistency

5. PROPOSED SOLUTION

Blood slides are treated with Anti-A, Anti-B, and Anti-D reagents. Based on the reaction, agglutination (clumping) occurs, which helps in identifying the blood group. The system captures these images and processes them step by step.

The overall flow of the system is:

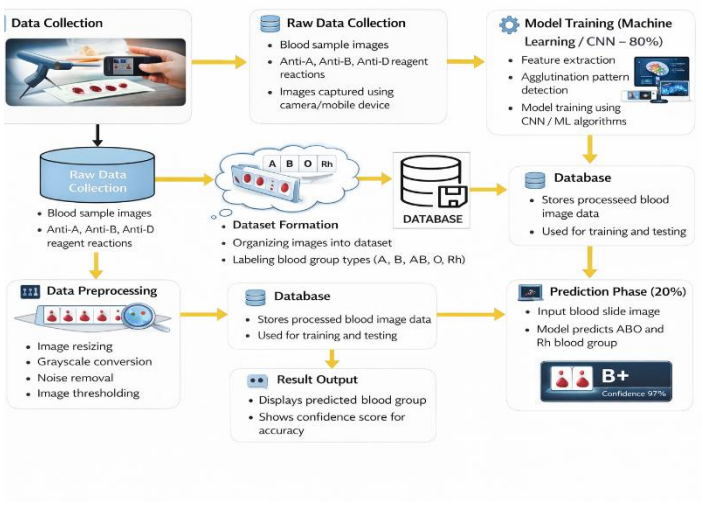
Input Image → Preprocessing → Feature Extraction → Classification → Output

This system reduces human errors and provides accurate and fast results, especially useful in medical emergencies.

6.Advantages of Proposed System

- Provides fast and automatic blood group detection
- Reduces human errors and improves accuracy
- Requires less manual effort
- Gives consistent and reliable results
- Useful in emergency situations for quick decisions
- Can handle large number of samples efficiently

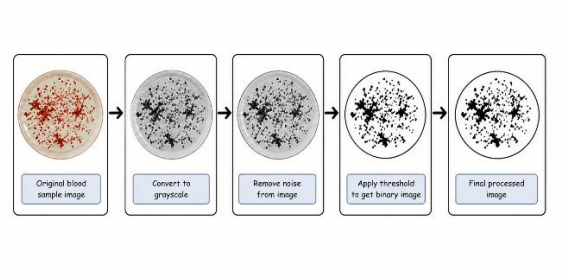
7.ARCHITECTURE DIAGRAM



8. METHODOLOGY

The system processes blood sample images in a sequence of steps. First, the image is captured and converted into grayscale to simplify analysis. Noise is removed and thresholding is applied to enhance the image quality. Then, important features such as agglutination patterns are extracted. Finally, machine learning and deep learning models like SVM and CNN are used to classify the blood group accurately.

8.1 Image Preprocessing



The input image is improved for better analysis. It includes:

- Converting the image into grayscale
- Removing noise using filters
- Applying thresholding

These steps help in making the image clear and suitable for further processing.

8.2 Feature Extraction

In this stage, important features are identified from the image. The system detects agglutination patterns by analyzing:

- Clump formation
- Intensity variation

These features help in understanding the blood group type.

8.3 Classification

The extracted features are classified using:

- Support Vector Machine (SVM): Used for basic classification
- Convolutional Neural Network (CNN): Used for higher accuracy

CNN automatically learns patterns and improves performance.

9. Results and Discussion

The proposed system produces accurate results by analyzing agglutination patterns. Compared to traditional methods, it reduces time and improves reliability. The system performs well when the input image is clear and properly processed.

It helps in minimizing human errors and provides consistent output. The performance can vary if the image quality is poor or if the sample is not properly prepared. Overall, the system shows good efficiency and practical usability.

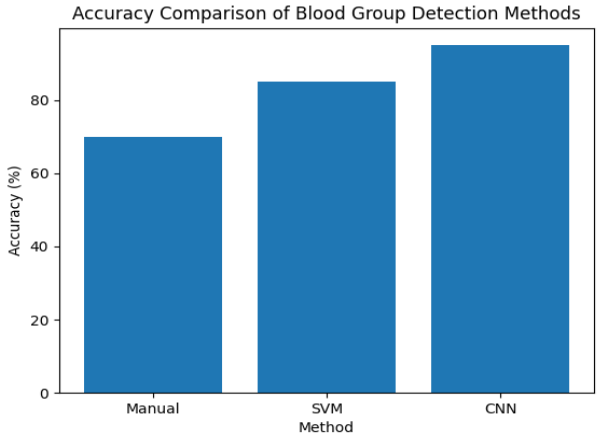


Fig. 1 Accuracy Comparison of Blood Group Detection Methods

10. Conclusion and Future work

This work presents an automated system for blood group detection using image processing and deep learning. It improves accuracy, reduces manual effort, and provides faster results than traditional methods. In future, the system can be enhanced using advanced models and larger datasets to improve performance. It can also be developed as a mobile application and made more effective for low-quality images.

11.Acknowledgment

The authors would like to thank their project guide and department for their continuous support and guidance. Their encouragement helped in completing this project successfully.

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AGRICULTURAL CROP AND FERTILIZER RECOMMENDATION USING SOIL AND CLIMATE PARAMETERS WITH GRADIENT BOOSTING AND GENERATIVE AI

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ABSTRACT

Agriculture is one of the most important sectors for food production and economic growth, but many farming decisions are still made using general practices rather than exact soil and environmental conditions. Incorrect crop selection and improper fertilizer usage may reduce productivity, damage soil quality, and increase farming risk. To overcome these problems, this project presents an intelligent Agricultural Crop and Fertilizer Recommendation System that provides data-driven support for better agricultural decision-making. The system considers major input factors such as soil nutrients, pH, temperature, humidity, rainfall, and soil image input to generate suitable crop and fertilizer recommendations. The proposed system is developed as a web-based application that combines machine learning, deep learning, and advisory support features. It helps users identify suitable crops for cultivation and provides fertilizer recommendations based on the given soil and climate values. A Convolutional Neural Network (CNN) is used for soil image classification, which improves the accuracy of soil-related analysis. The system also includes interactive advisory support and multilingual response generation, making it more practical and easier for users to understand. The application is implemented using Python, Flask, and MySQL, and it includes modules for user interaction, recommendation generation, soil image analysis, feedback handling, and chat support. By integrating intelligent prediction and user-friendly communication, the system helps improve crop planning, support better fertilizer management, reduce uncertainty in farming decisions, and encourage sustainable agricultural practices.

Keywords: *Crop Recommendation, Fertilizer Recommendation, Soil Analysis, Machine Learning, Deep Learning, CNN, LightGBM, Flask, MySQL, Sustainable Farming*

I. INTRODUCTION

Agriculture remains a fundamental sector for food production, economic stability, and rural livelihood, especially in developing regions where farming plays a central role in daily life. However, agricultural decision-making is still often based on generalized recommendations, traditional knowledge, and manual interpretation of soil conditions rather than field-specific analysis. As a result, farmers may select unsuitable crops or apply fertilizers without accurately understanding the nutrient status of the soil, which can lead to lower productivity, soil degradation, and inefficient resource utilization.

Recent advances in intelligent computing have created new opportunities to improve agricultural planning through data-driven systems. By analyzing soil nutrients, climatic conditions, and related agricultural inputs, machine learning models can support more accurate crop and fertilizer recommendations. Such approaches are valuable because they reduce dependence on guesswork and help transform raw agricultural data into practical guidance. In addition, deep learning techniques have shown strong potential in image-based agricultural analysis, enabling visual soil information to be used alongside numerical inputs for improved decision support.

In this context, the proposed work presents an intelligent Agricultural Crop and Fertilizer Recommendation System that combines structured soil and climate analysis with soil image classification. The system considers important parameters such as Nitrogen, Phosphorus, Potassium, pH, temperature, humidity, and rainfall to recommend suitable crops and fertilizers. A Convolutional Neural Network (CNN) is used for soil image classification, which strengthens the recommendation process by incorporating visual soil characteristics. The system also includes interactive advisory support and multilingual response generation to improve usability and accessibility for different users.

The proposed system is implemented as a web-based platform so that users can easily provide inputs, obtain recommendations, and interact with the advisory module in a practical environment. By integrating intelligent recommendation, soil image analysis, and user-friendly communication support, the system aims to improve crop planning, fertilizer management, and sustainable farming practices. Thus, this work contributes toward the development of a more accessible and data-driven agricultural decision-support framework.

II. PROBLEM STATEMENT

Many farmers and agricultural users face difficulties in selecting suitable crops and fertilizers because farming decisions are often based on traditional practices, generalized recommendations, and manual interpretation of soil reports. In many cases, field-specific soil and climate data are not effectively used for decision-making, which leads to incorrect crop selection, improper fertilizer usage, low productivity, and soil imbalance. Existing approaches may also lack user-friendly guidance, image-based soil analysis, and interactive support, making it difficult for users to convert raw agricultural data into practical actions. These issues reduce decision accuracy and affect sustainable farming outcomes.

Specifically, the core problems identified are:

- Dependence on manual soil testing and expert interpretation for crop and fertilizer decisions.
- Lack of field-specific and data-driven crop recommendation support.
- Improper fertilizer usage due to generalized or assumption-based practices.
- Limited integration of soil image analysis with numerical agricultural inputs.
- Absence of simple interactive advisory support for users.
- Difficulty in accessing understandable recommendations in different languages through a single platform.

III. EXISTING SYSTEMS AND LIMITATIONS

The existing agricultural support systems mainly rely on manual soil testing, traditional farming practices, and generalized recommendations provided through reports or local guidance. Although these methods provide some level of assistance, they exhibit several important limitations.

First, they lack field-specific intelligence, as the same recommendations are often applied to different farms without considering exact soil and climate conditions. Second, converting soil test values such as Nitrogen, Phosphorus, Potassium, and pH into practical crop and fertilizer decisions usually requires expert interpretation, which is not always easily available to farmers.

Third, many traditional and earlier digital systems do not include image-based soil analysis, interactive advisory support, or multilingual accessibility, making them less practical for real-time use. Fourth, existing methods often depend on assumptions or fixed schedules for fertilizer usage, which may lead to overuse, underuse, and reduced soil productivity. These limitations highlight the need for an integrated, intelligent, and user-friendly agricultural recommendation system that can provide accurate crop and fertilizer suggestions based on soil, climate, and image-based inputs.

IV. PROPOSED SYSTEM: MATELEARN

A. System Architecture & Technologies

The proposed system is an intelligent web-based

agricultural recommendation platform that integrates machine learning, deep learning, and advisory support within a unified architecture. The system follows a modular design using a frontend interface, Flask-based backend, and MySQL database to ensure organized processing, scalability, and efficient data management.

The frontend is developed using HTML, CSS, and JavaScript to provide a simple and user-friendly interface. The backend is implemented using Python and Flask, which handle user requests, input processing, recommendation logic, and interaction between the various modules. MySQL is used as the primary database for storing user details, fertilizer-related records, feedback, and chat logs.

A dedicated prediction and analysis layer supports intelligent system functions such as crop recommendation, fertilizer suggestion, soil image classification, and explainable output generation. This modular structure ensures that each component performs a specific function while remaining seamlessly integrated with the others.

B. Intelligent Recommendation and Soil Analysis

The proposed system allows users to enter important agricultural parameters such as Nitrogen, Phosphorus, Potassium, pH, temperature, humidity, and rainfall. Based on these inputs, the system analyzes the data and generates suitable crop and fertilizer recommendations. This reduces dependence on generalized agricultural practices and helps users make more accurate farming decisions.

In addition to numerical analysis, the system also supports soil image classification. Users can upload soil images, which are processed using a Convolutional Neural Network (CNN) model to identify the soil type. This image-based analysis strengthens the recommendation process by combining visual soil information with numerical soil and climate parameters.

C. Advisory Support and Explainable Output

The system includes chatbot-based advisory support to improve user interaction and make recommendations easier to understand. Users can submit soil-related queries, crop names, fertilizer names, or parameter values, and the chatbot provides meaningful responses based on the available data and system logic. This feature makes the application more interactive and practical for agricultural usage.

To improve transparency, the system also supports explainable output analysis using SHAP. This helps indicate how different input parameters influence the final result, making the recommendation process more understandable and trustworthy for users.

D. Accessibility and User Management

The system supports multilingual response generation so that recommendations can be presented in different languages according to user preference. This improves accessibility and usability for a wider range of users.

The platform also manages user registration, login, feedback submission, and chat log maintenance through secure and organized system modules. By combining intelligent recommendation, soil image analysis, advisory support, and multilingual communication, the proposed system provides a practical, scalable, and user-friendly solution for crop planning, fertilizer management, and sustainable farming practices.

V. ALGORITHM FOR AI-ASSISTED SMART LEARNING

The proposed system follows a multi-stage intelligent processing flow for crop and fertilizer recommendation.

Stage 1 — Input Collection:

The system collects agricultural input values from the user, including Nitrogen, Phosphorus, Potassium, pH, temperature, humidity, and rainfall. It also accepts soil image input for image-based soil analysis.

Stage 2 — Data Processing:

The input values are validated and prepared for analysis. Numerical soil and climate parameters are organized into a structured format so that they can be used effectively by the recommendation and prediction modules.

Stage 3 — Crop Recommendation:

The processed agricultural inputs are analyzed using intelligent recommendation logic to identify the most suitable crop for cultivation. This stage supports better crop planning based on soil and environmental conditions.

Stage 4 — Fertilizer Recommendation:

After crop-related analysis, the system retrieves the appropriate fertilizer recommendation from the dataset or database based on the crop type and soil-related conditions. This helps users select suitable fertilizer support for better productivity.

Stage 5 — Soil Image Classification:

If the user uploads a soil image, the Convolutional Neural Network (CNN) model processes the image and predicts the soil type. This image-based result strengthens the overall recommendation by combining visual soil information with numerical input values.

Stage 6 — Advisory Support and Output Generation:

The system generates the final output in a user-friendly format. Chatbot-based advisory support and multilingual response generation are also provided to make the recommendation more understandable and accessible.

Feedback and chat interactions are maintained for system support and future reference.

VI. TECHNOLOGIES USED

The proposed Agricultural Crop and Fertilizer Recommendation System uses a suitable technology stack to support data processing, recommendation generation, soil image analysis, and web-based interaction.

Frontend:

HTML, CSS, and JavaScript are used to develop the user interface of the system. These technologies help create a simple and interactive web environment for user input and result display.

Backend:

Python is used as the core programming language, and Flask is used as the backend web framework to handle system logic, routing, recommendation processing, and module integration.

Database:

MySQL is used as the database for storing user details, fertilizer-related records, feedback data,

and chat logs.

Machine Learning and Deep Learning:

LightGBM is used for predictive analysis and recommendation support. Convolutional Neural Network (CNN) is used for soil image classification. Scikit-learn supports recommendation-related utilities, and SHAP is used for explainable output analysis.

Data Processing Libraries:

Pandas and NumPy are used for data handling, preprocessing, and numerical computation. OpenCV, TensorFlow, and Keras are used for image processing and deep learning-based soil analysis.

Development Tools:

Visual Studio Code or Python IDLE can be used for coding and debugging. The system is developed and tested in a Windows environment

VII. EXPECTED OUTCOMES

The proposed Agricultural Crop and Fertilizer Recommendation System is expected to deliver significant agricultural and technical outcomes.

Agricultural Impact:

The system will support users in selecting suitable crops based on soil and climate conditions, thereby improving crop planning and reducing uncertainty in farming decisions. By providing appropriate fertilizer recommendations, it will also help in better nutrient management and improved agricultural productivity.

Soil and Resource Management:

The system will promote efficient fertilizer usage and help maintain soil fertility by reducing overuse or underuse of fertilizers. Soil image classification and soil-related analysis will further strengthen the understanding of soil condition, supporting better land and resource management.

Accessibility and Usability:

Through chatbot-based advisory support and multilingual response generation, the system will make agricultural recommendations easier to understand and more accessible to different users. The web-based interface will provide a simple and user-friendly environment for interacting with the system.

Technical Contribution:

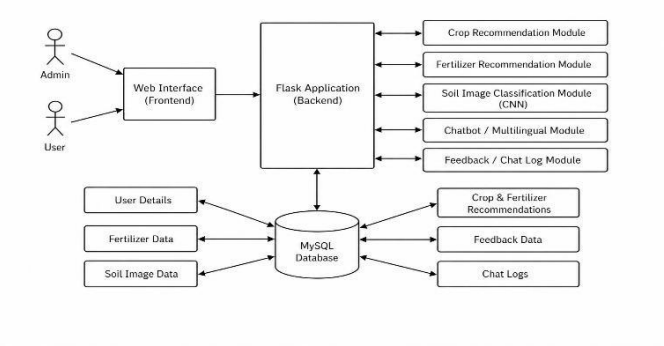
The project will demonstrate the effective integration of machine learning, deep learning, soil image classification, explainable analysis, and web technologies into a practical agricultural recommendation platform. It will also provide a strong foundation for future enhancements in intelligent farming support systems and data-driven agricultural applications.

VIII. SYSTEM DESIGN OVERVIEW

The architectural design of the proposed Agricultural Crop and Fertilizer Recommendation System follows a modular web-based structure in which different functional components work together as an integrated platform. The user interacts with the system through a web interface developed using HTML, CSS, JavaScript, and Flask templates. The backend is implemented using Python and Flask, which handle user requests, input processing, recommendation logic,

soil image classification, advisory support, and communication with the database.
system includes two primary actors: the **Admin** and the **User**. The main functions of the system include user registration and login, entering soil and climate parameters, uploading soil images, obtaining crop recommendations, receiving fertilizer suggestions, interacting with the chatbot, viewing multilingual output, submitting feedback, and managing chat logs and fertilizer data. These modules are designed in a way that each functional component performs a dedicated role while remaining connected to the others.

The modular structure of the system improves maintainability, scalability, and usability. The crop recommendation, fertilizer recommendation, soil image classification, chatbot support, multilingual response generation, and database management modules can operate together efficiently to provide a practical agricultural support environment. MySQL is used as the backend database for storing user details, fertilizer-related records, feedback entries, and chat logs. Overall, the system design ensures smooth integration, efficient data handling, and user-friendly operation for intelligent agricultural decision-making.



IX. CONCLUSION

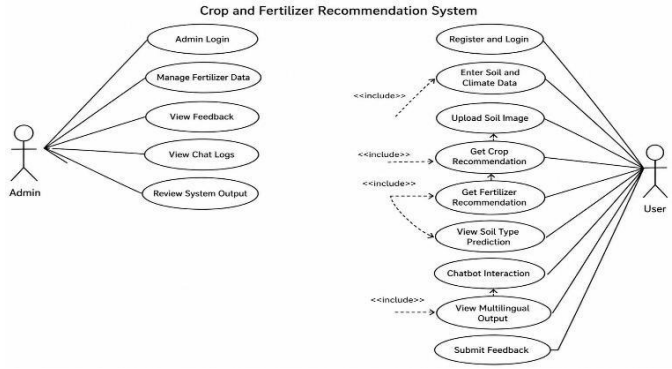
The proposed Agricultural Crop and Fertilizer Recommendation System provides an intelligent and practical solution for modern farming by using soil and climate parameters for better decision-making. The system helps users identify suitable crops and appropriate fertilizer recommendations based on inputs such as soil nutrients, pH, temperature, humidity, and rainfall. It also supports soil image classification, which improves the analysis process by combining visual and numerical inputs.

The integration of machine learning, deep learning, chatbot-based advisory support, and multilingual response generation makes the system more user-friendly and effective for agricultural use. By providing accurate recommendations through a web-based platform, the system helps improve crop planning, fertilizer management, and overall farming efficiency.

This project reduces uncertainty in agricultural decision-making and promotes sustainable farming practices through intelligent analysis and accessible user interaction. In the

future, the system can be further enhanced with additional agricultural modules and expanded data support to improve its performance and practical value.

Use-Case Diagram



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AI Based Induction Motor Maintenance Prediction System

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Abstract: Induction motors are widely used in industries for running machines in sectors like manufacturing, agriculture, and energy. However, these motors often face problems such as overheating, vibration, electrical faults, and wear and tear, which can lead to sudden failure and high maintenance cost. Traditional maintenance methods based on regular checking or repairing after failure are not efficient. This project presents an AI Based Induction Motor Maintenance Prediction System using IoT and machine learning for smart monitoring. The system uses ESP32 along with sensors like DS18B20, ACS712, voltage sensors, and ADXL345 to collect important motor data. This data is sent through MQTT to Raspberry Pi, where it is analyzed using scikit-learn. The system can detect faults early, predict Remaining Useful Life (RUL), and take preventive actions. A Flask-based dashboard shows real-time data, helping to reduce downtime and improve motor performance.

Keywords: Induction Motor, Predictive Maintenance, ESP32, IoT, Machine Learning, scikit-learn, MQTT, Raspberry Pi, Vibration Analysis, Remaining Useful Life (RUL)

1. INTRODUCTION

Induction motors are important in industries as they run machines in areas like manufacturing, energy, agriculture, and construction. They are strong and efficient, but over time they can face problems such as wear and tear, electrical faults, and environmental effects. These issues can cause sudden failure, leading to production loss, high maintenance cost, and safety risks. Therefore, real-time monitoring and predictive maintenance are necessary.

Traditional maintenance methods like manual inspection and scheduled servicing are not fully reliable. They take more time, need human effort, and may miss hidden faults. To solve this problem, modern systems use IoT (Internet of Things) and Artificial Intelligence (AI) for smart monitoring.

Predictive maintenance works by continuously checking motor parameters, analyzing data, and predicting faults before failure occurs. This helps in planning maintenance, reducing downtime, and increasing motor life. IoT collects real-time data from sensors, while machine learning analyzes patterns and predicts Remaining Useful Life (RUL).

In this project, ESP32 collects data from DS18B20, ACS712, voltage sensors, and ADXL345. The data is sent to Raspberry Pi using MQTT for analysis and monitoring. A Flask-based dashboard shows real-time data and alerts. The system improves safety, reduces cost, and supports Industry 4.0 with smart and automated maintenance.

1.1 Problem Definition:

In industrial applications, induction motors are important for running machines and production processes. Even though they are reliable, they can face problems like mechanical wear, electrical faults, overheating, overload, and vibration. These issues can cause sudden motor failure, leading to production loss, high maintenance cost, and safety risks. Traditional maintenance methods such as manual inspection and reactive repair are not effective in detecting early faults.

Another issue is the lack of real-time monitoring and predictive analysis. Many industries follow fixed maintenance schedules without checking the actual condition of the motor. This results in either unnecessary maintenance or delayed action, increasing cost and risk. Unplanned downtime also affects production and overall efficiency. Modern industries require smart solutions for continuous monitoring. However, many existing systems are expensive and not suitable for small-scale industries. Therefore, this project focuses on developing an IoT and AI-based system that can monitor motor health, detect faults, predict Remaining Useful Life (RUL), and provide real-time alerts with automatic protection to improve reliability and reduce downtime.

1.2 Need of Project

In industries, induction motors are widely used to run machines like pumps, compressors, and production systems. However, problems such as overheating, overcurrent, voltage fluctuation, mechanical wear, and vibration can cause sudden failures. These failures lead to downtime, financial loss, and safety risks. Traditional maintenance methods like periodic inspection are not enough to detect early faults.

There is a need for a smart system that can continuously monitor motor parameters such as temperature, current, voltage, and vibration. Real-time monitoring helps in identifying problems early and taking timely action. It also helps in predicting Remaining Useful Life (RUL), which allows better maintenance planning and reduces unnecessary costs.

Another important need is safety. Abnormal motor conditions can damage equipment or cause accidents. An automatic protection system can prevent serious failures.

This project also supports Industry 4.0 by using IoT and AI for smart monitoring, data analysis, and better decision-making. It provides a cost-effective and reliable solution for improving motor performance and reducing downtime.

1.3. Aim:

The aim of this project is to design and build an IoT and AI-based system for real-time monitoring of motor health and predictive maintenance. The system focuses on measuring parameters such as temperature, current, voltage, and vibration, detecting faults at an early stage, and avoiding motor failure using alerts and protection.

1.4. Objectives:

- To develop a system for real-time monitoring of motor temperature, current, voltage, and vibration
- To use ESP32 and MQTT for wireless data communication
- To collect and store sensor data for analysis and predictive maintenance
- To apply machine learning methods for fault detection and failure prediction
- To use a relay mechanism for automatic motor protection during abnormal conditions
- To create a user-friendly web dashboard for live data, alerts, and insights
- To reduce downtime and maintenance cost using predictive and preventive actions

2. CONSTRUCTION AND WORKING

The block diagram shows the working structure of the Intelligent Motor Health Monitoring and Predictive Maintenance System using IoT and Machine Learning. The ESP32 microcontroller is the main unit of the system, which collects, processes, and sends sensor data. It receives power from the Power Supply Unit to ensure stable operation of all components.

Different sensors are connected to the ESP32 to monitor motor health in real time. The DS18B20 temperature sensor measures the motor surface temperature to detect overheating. The ACS-based Current Sensor checks the current consumption to identify overload or abnormal conditions. The Voltage Sensor monitors the supply voltage to detect under-voltage or over-voltage, which can affect motor performance.

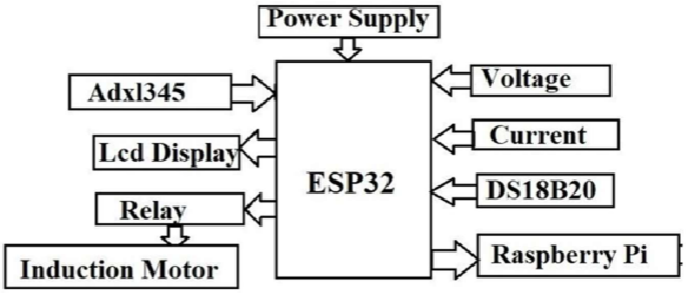

Figure 1: Block diagram

The ADXL345 accelerometer is used as a vibration sensor to detect mechanical problems in the motor. It measures vibration patterns, which help in identifying issues like imbalance, misalignment, and bearing faults. All sensor values are also shown on an LCD display, so operators can check the motor condition directly.

For protection, the ESP32 controls a Relay Module connected to the induction motor. If abnormal conditions such as high temperature, high vibration, or overcurrent are detected, the relay automatically cuts off the motor supply to avoid damage. The system also communicates with a Raspberry Pi, which works as a data server and machine learning unit. Sensor data is sent through the MQTT protocol for storage and analysis.

Overall, the system works as an integrated solution where ESP32 collects and displays data, sends it to Raspberry Pi for processing, and protects the motor using automatic relay control. This setup enables real-time monitoring and predictive maintenance in industrial applications.

Components used:

Hardware List

1. **ESP32 Microcontroller** – Used as the main IoT controller to collect sensor data and send it to Raspberry Pi using MQTT.
2. **Raspberry Pi 4 (4GB)** – Works as a central server for data storage, machine learning processing, and running the Flask web dashboard.
3. **DS18B20 Temperature Sensor** – Measures the motor surface temperature to detect overheating.
4. **ACS712 Current Sensor** – Measures the current used by the motor to identify overload or short circuit conditions.
5. **Voltage Sensor Module** – Monitors the input supply voltage to detect over-voltage or under-voltage.
6. **ADXL345 Accelerometer (Vibration Sensor)** – Measures vibration to detect problems like imbalance, misalignment, and bearing faults.
7. **Relay Module** – Disconnects motor power automatically during abnormal conditions to protect the system.
8. **LCD Display (I2C Interface)** – Displays real-time values such as temperature, voltage, current, vibration, and motor status.
9. **DC Motor or Induction Motor Setup** – Used as a test motor for checking system performance and validation.
10. **Power Supply Unit** – Provides required power to ESP32, sensors, and the motor system.

Software List

1. **Arduino IDE** – Used to write, compile, and upload programs to the ESP32 microcontroller.
2. **Python 3 (on Raspberry Pi)** – Used for data processing, machine learning, and dashboard development.

3 **MQTT Protocol (Mosquitto Broker)** – Used for communication between ESP32 and Raspberry Pi.
4 **scikit-learn Library** – Used to train machine learning models for fault detection and Remaining Useful Life (RUL) prediction.
5 **Flask Framework** – Used to develop a web dashboard for showing live data, analysis, and alerts.
6 **CSV File Storage** – Used to store sensor data for future analysis and machine learning.
7 **Raspbian OS** – Operating system used on Raspberry Pi to run and manage all software processes.

3. METHODOLOGY AND SYSTEM SETUP

The methodology of the Intelligent Motor Health Monitoring and Predictive Maintenance system explains the steps followed to design and implement the system. It includes hardware setup, data collection, machine learning analysis, motor protection, and web monitoring.

1. System Design and Planning

First, important motor parameters like temperature, current, voltage, and vibration were selected for monitoring. Suitable sensors such as DS18B20, ACS712, voltage sensor module, and ADXL345 were chosen based on accuracy and cost. ESP32 was used for data collection due to its Wi-Fi support, while Raspberry Pi 4B was selected for data processing, storage, and dashboard display. A proper data flow was planned from sensors to analysis and protection.

2. Hardware Setup

All sensors were connected to the ESP32 using analog and I2C pins, and communication was set using MQTT. The DS18B20 sensor was placed on the motor to measure temperature. The ACS712 sensor was connected in series to measure current. The voltage sensor monitored supply voltage, and the ADXL345 sensor was fixed on the motor to measure vibration. The relay module is connected between the motor power supply and the ESP32 digital pin. It is programmed to turn ON during abnormal conditions to protect the motor. An LCD display with I2C interface is used to show motor parameters locally. A power supply unit provides 5V DC for ESP32, sensors, and LCD, while the motor and relay use the required higher voltage.

3. Sensor Calibration

All sensors are calibrated to improve accuracy. The DS18B20 temperature sensor is checked using a digital thermometer. The ACS712 current sensor is compared with a multimeter reading. The voltage sensor is calibrated by converting ADC values into actual voltage using a resistive divider. The ADXL345 vibration sensor is set by measuring normal motor vibration and fixing a threshold for abnormal conditions.

4. Software Implementation

The ESP32 is programmed using Arduino IDE to read sensor data, display it on LCD, send data through MQTT, and control the relay. The Raspberry Pi runs Python programs to receive data, store it in CSV files, and process it. Machine learning using scikit-learn is applied for fault detection and Remaining Useful Life (RUL) prediction. A Flask-based dashboard is used to show live data, alerts, and analysis.

5. Data Acquisition

The ESP32 collects sensor data every 1 second and sends it via MQTT. The Raspberry Pi stores this data in CSV format for historical analysis, machine learning training, and dashboard visualization.

6. Data Preprocessing

The collected data is prepared before analysis. Noise is reduced using a moving average method. Data is normalized for machine learning input, and missing or incorrect readings are handled to improve accuracy.

7. Machine Learning Analysis

Stored data is analyzed to understand patterns of normal and faulty motor operation. Machine learning models are used for fault detection and Remaining Useful Life (RUL) prediction. Random Forest Classifier is applied for fault detection, while Linear Regression or SVR (Support Vector Regression) is used for RUL estimation. Based on these results, threshold values are set to activate the relay when needed.

8. Motor Protection

The relay module automatically disconnects the motor when unsafe conditions occur, such as high temperature, excess current, voltage variation, or high vibration. This helps to prevent motor damage, fire risk, and mechanical failure.

9. Dashboard Visualization

A Flask-based web dashboard is used to display live sensor data like temperature, current, voltage, and vibration. It also shows alerts, historical graphs, and predicted Remaining Useful Life (RUL). This allows remote monitoring and helps operators take quick and effective actions.

10. System Testing and Validation

The system was tested using a small induction motor under different load conditions. Sensor readings were checked by comparing them with standard measuring instruments to ensure accuracy. Different fault conditions such as overload, overvoltage, overheating, and high vibration were created to test relay operation and alert generation. Machine learning results were also verified using real and historical data.

11. Iterative Improvements

Based on testing results, system thresholds and machine learning models were updated. Sensor positions were adjusted for better accuracy, and the dashboard design was improved for clear and easy understanding of motor data and alerts.

12. Safety Considerations

Proper safety measures were taken during design. Electrical isolation between ESP32 and motor was ensured using a relay module. Fuses and resistors were used to avoid short circuits. Grounding and insulation were checked for safe operation, and all components were tested before final use.

13. Final Integration

All hardware components were assembled on a prototype board or control panel. Software modules were integrated for continuous operation. The system works in a loop, where it collects data, sends it, analyzes it, displays results, and protects the motor in real time.

4. ADVANTAGES AND LIMITATIONS.

4.1.Advantages:

1. Provides real-time monitoring of motor parameters like temperature, current, voltage, and vibration.
2. Protects the motor automatically using a relay during abnormal conditions.
3. Supports predictive maintenance, which helps reduce downtime and maintenance cost.
4. Uses low-cost components like ESP32, sensors, and Raspberry Pi, making it affordable.
5. Stores historical data for performance analysis and better decision-making.
6. Machine learning helps in predicting Remaining Useful Life (RUL) for proper maintenance planning.
7. Allows remote monitoring through a Flask-based web dashboard.

4.2.Limitations:

1. Low-cost sensors like DS18B20, ACS712, and ADXL345 may not give highly accurate results in harsh industrial conditions.
2. The system stores data locally in CSV files, so remote access is limited.
3. ESP32 Wi-Fi works only within a local network; cloud integration is not included.
4. Machine learning models need regular retraining to maintain accuracy.
5. The system depends on the MQTT broker, so network failure can stop data transfer.
6. Testing is done on a prototype motor, which may not fully match real industrial motors.
7. The setup requires proper knowledge of hardware and software integration.
8. Relay-based protection may have slight delay if thresholds are not properly set.
9. ESP32 and sensors may not perform well in high temperature, vibration, or dusty environments.
10. Complex faults like rotor bar damage or winding insulation issues may need advanced sensors.

5. CONCLUSION

The intelligent Motor Health Monitoring and Predictive Maintenance system combines IoT, sensors, and machine learning to monitor and protect induction motors in real time. It continuously measures temperature, current, voltage, and vibration to detect abnormal conditions and estimate the Remaining Useful Life (RUL) of the motor.

The ESP32 collects sensor data, and the Raspberry Pi processes it using machine learning and displays the results on a Flask web dashboard. A relay system automatically protects the motor during fault conditions, helping to reduce downtime and maintenance cost. This system provides a cost-effective, scalable, and smart solution for motor maintenance, supporting Industry 4.0 concepts. With future improvements, it can be expanded for monitoring multiple motors and larger industrial systems.

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Campus Placement Requirement and Mock Test System

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Abstract

The Campus Placement Preparation and Mock Test System is a web-based platform designed to help undergraduate and postgraduate students prepare effectively for campus recruitment and competitive job selection. The system is developed using Python (Flask framework), along with HTML, CSS, JavaScript, and SQLite. It consists of fourteen integrated modules that support various aspects of placement preparation, including aptitude tests, technical assessments, coding practice, resume creation, interview guidance, performance tracking, and administrative management.

To provide a realistic experience, the platform offers time-bound mock tests that simulate actual placement exams, with automatic evaluation and instant result generation. It also includes detailed performance analysis, such as topic-wise accuracy and difficulty-level insights, enabling students to identify their strengths and areas for improvement. The results from testing and usage indicate that this centralized system significantly enhances students' readiness for placements. This paper discusses the system architecture, database structure, module design, implementation process, and evaluation results, following IEEE journal standards.

Keywords— Campus placement, mock test system, Flask framework, SQLite, performance analytics, resume builder, web-based platform, aptitude assessment

I. Introduction

Campus placement is an important milestone in a student's academic journey, particularly for those pursuing professional and technical education. In today's competitive job market, students are expected to go beyond academic performance and demonstrate strong aptitude, technical knowledge, and problem-solving abilities. However, many students struggle with preparation due to the lack of structured guidance, limited access to quality practice resources, and insufficient exposure to real placement scenarios.

To overcome these challenges, there is a clear need for a centralized and technology-enabled solution that can support students throughout their preparation process. The Campus Placement Preparation and Mock Test System is developed as a web-based platform that offers a comprehensive environment for placement readiness. It brings together various essential components such as aptitude testing, technical assessments, coding practice, resume development, and interview preparation into a single system. By doing so, it minimizes the need for multiple external tools and provides a more organized and efficient learning experience.

The system is built using Python with the Flask framework, along with front-end technologies like

HTML, CSS, and JavaScript, and uses SQLite for managing data efficiently. A key feature of the platform is its ability to replicate real placement exam conditions through time-bound mock tests, supported by automatic evaluation and instant feedback. In addition, the system includes performance analytics that help students monitor their progress, understand their strengths, and identify areas that need improvement.

The main goal of this platform is to improve students' readiness for campus recruitment by offering a structured, accessible, and user-friendly preparation system. This paper presents the overall design, implementation approach, and evaluation of the system, demonstrating its effectiveness in enhancing placement preparation.

II. Related Works

Several research efforts have focused on developing technology-driven solutions for placement preparation and online examination systems. Bharadwaj and Pal [1] introduced an e-learning platform aimed at improving aptitude skills; however, their system did not include features such as resume management or company-specific preparation modules. Similarly, Kumar et al. [2] designed an online examination system using PHP and MySQL, but it lacked advanced capabilities like

performance analytics and integrated coding environments.

Desai and Trivedi [3] developed a campus recruitment portal that primarily focused on administrative processes, with limited support for student-side preparation activities. In contrast, studies by Goyal and Mittal [4] highlighted the effectiveness of adaptive testing techniques in enhancing student performance, emphasizing the importance of analytics-driven learning systems.

In addition, widely used Learning Management Systems (LMS) such as Moodle and Blackboard demonstrate the benefits of integrated digital platforms for education. However, these systems are generally designed for broad academic use and do not provide specialized features required for campus placement preparation, such as company-specific mock tests, coding assessments, and placement notification modules [5].

To overcome these limitations, the proposed system offers a dedicated and comprehensive platform tailored specifically for placement preparation. It integrates real-time feedback mechanisms, role- based access control, and institution-specific customization, thereby delivering a more focused and effective solution for students and administrators

III SYSTEM REQUIREMENTS

A. .HARDWARE REQUIREMENTS

Component	Specification
Processor	Dual Core 2.4 GHz+
Monitor	15 Vga Color
RAM	16 GB
Storage	512 GB+

B. SOFTWARE REQUIREMENTS

Component	Specification
Backend	Python 3.x + Flask
Database	SQLite
IDE	VS Code / Notepad++
OS	Windows 10

PROPOSED SYSTEM

1. Centralized Web-Based Platform

➢ The proposed system provides a unified, web-based platform that integrates all campus placement activities into a single interface. It allows seamless interaction between students, placement officers, and recruiters, ensuring efficient management of placement processes and preparation resources.

2. Student Registration and Profile Management

➢ Students can create secure accounts and maintain comprehensive profiles that include academic records, technical skills, certifications, and resumes. The system enables easy updating of information, ensuring that student data remains accurate and accessible for recruitment processes.

3. Mock Tests for Placement Preparation

➢ The system offers structured mock tests designed to simulate real campus recruitment exams. These tests cover key areas such as aptitude, logical reasoning, and technical knowledge, helping students familiarize themselves with exam patterns and improve their performance.

4. Coding Practice Module

➢ A dedicated coding environment allows students to practice programming problems across various difficulty levels. This feature helps enhance problem-solving abilities, coding efficiency, and prepares students for technical interview rounds.

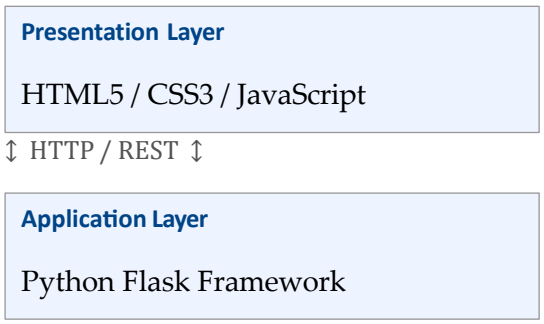
Automated Evaluation and Instant Results

Component	Specification
Frontend	HTML, CSS,

➢ The system automatically evaluates test responses and generates instant results. This eliminates manual checking, reduces errors, and provides immediate feedback to students, enabling them to track their progress in real time.

5. Performance Analysis and Insights

➢ Advanced analytics tools provide detailed performance reports, including score breakdowns, accuracy levels, and topic- wise analysis. This helps students identify their strengths and weaknesses and focus on areas that need improvement



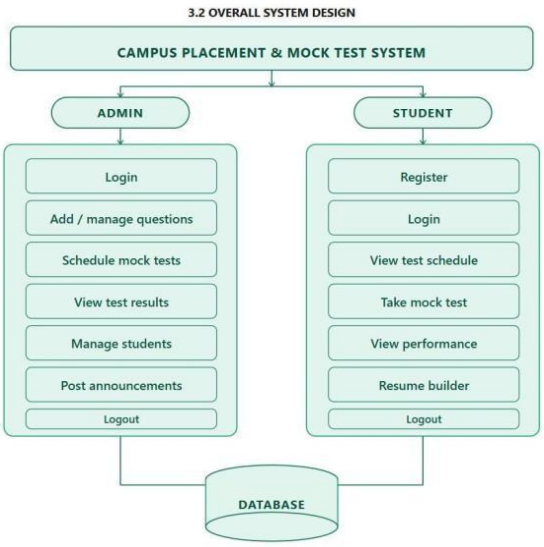
B.DATABASE DESIGN

Field	Data Type	Description
user_id	INTEGER PK	Auto-increment primary key
Name	VARCHAR(100)	Student full name
Email	VARCHAR(100)	Unique login email
Password	TEXT	PBKDF2 hashed password
Role	VARCHAR(20)	student / admin
College	VARCHAR(100)	Institution name

TABLEI UsersTable Schema

Data Layer

SQLite Relational Database



IV A SYSTEM DESIGN

	Data Type	Description
question_id	INTEGER PK	Auto-increment primary key
Category	VARCHAR(50)	aptitude / technical
Subject	VARCHAR(50)	Quantitative, DBMS, etc.
Difficulty	VARCHAR(20)	easy / medium / hard
correct_answer	VARCHAR(5)	Option key (A–D)
Explanation	TEXT	Solution explanation

Field	Data Type	Description
result_id	INTEGER PK	Auto-increment primary key
student_id	INTEGER FK	References users table
test_id	INTEGER FK	References tests table
Score	DECIMAL(5,2)	Percentage score achieved
correct_answers	INTEGER	Number of correct responses
Rank	INTEGER	Computed rank among peers

TABLE III. Test Results Table Schema

V System implementation

1) User Authentication Module: Handles secure registration and login with role-based session management and password encryption.

2) Dashboard Module: Provides a personalized interface displaying completed tests, scores, upcoming exams, and announcements.

3) Aptitude Test Module: Delivers time-bound tests covering quantitative aptitude, logical reasoning, and verbal ability with randomized questions.

4) Technical Assessment Module: Evaluates knowledge in DBMS, Operating Systems, Computer Networks, and Programming with difficulty-leveled MCQs.

5) Coding Practice Module: Provides an integrated code editor supporting Python with real- time compilation, test-case evaluation, and difficulty filtering.

6) Mock Test Simulation Module: Replicates real placement exam conditions with countdown timers, section navigation, and automatic submission.

7) Performance Analytics Module: Delivers graphical performance reports including score

trends, category-wise accuracy, and improvement recommendations.

8) Resume Builder Module: Enables students to create ATS-friendly resumes using structured templates with sections for education, skills, projects, and certifications.

9) Interview Preparation Module: Provides HR and technical question banks, company-specific preparation guides, and soft-skill development resources.

10) Announcement Module: Disseminates placement updates and test schedules to all registered students in real time.

11) Company Preparation Module: Offers company-wise test patterns and selection round details for major recruiters including TCS, Infosys, Wipro, and Accenture.

12) Feedback Module: Collects student feedback with ratings and transmits it to administrators for quality improvement.

13) Retest Scheduling Module: Allows students to schedule reminder-based retests at 3, 6, or 12- month intervals for spaced-repetition learning.

14) Admin Control Module: Provides complete system management including user administration,question bank management, and report generation.

VI EXISTING SYSTEMS

A systematic analysis of current placement preparation practices reveals five critical limitations:

A. Decentralized Learning Resources

Students rely on multiple disconnected platforms including websites, textbooks, YouTube tutorials, and external coaching materials. This fragmented approach creates confusion, reduces efficiency, and makes it difficult to follow a structured study plan aligned with placement timelines.

B. Absence of Unified Assessment Infrastructure Existing mock tests are limited in scope and are not designed to replicate actual placement examination
patterns of target companies such as TCS, Infosys,
Wipro, Cognizant, and Accenture. This limits students' ability to practice in realistic conditions.

C. Lack of Performance Analytics

Current tools do not provide granular insight into topic-wise accuracy, speed, or improvement trends. Without actionable feedback, students cannot identify and address specific weaknesses, resulting in inefficient preparation strategies.

D. No Resume Development Support

Students are not provided with structured tools, templates, or expert guidance for professional resume creation. Poorly structured resumes reduce visibility in applicant screening processes.

E. Inadequate Administrative Coordination

Placement offices manage job postings, student applications, and test schedules through manual or standalone digital tools, leading to coordination inefficiencies and communication gaps between students and recruiters.

VII RESULTS AND DISCUSSION

A pilot evaluation was conducted with engineering students across multiple branches at SCSVMV University over a six-week period. Students were asked to use the platform for self-paced placement preparation and complete a post-study survey.

A. Usability

On a 5-point Likert scale, students rated the platform's ease of use at 4.3/5, navigation clarity at 4.5/5, and visual design at 4.1/5. The single-file Flask architecture resulted in sub- 200ms average page response times under typical load. The absence of a JavaScript framework contributed to fast initial page loads, particularly on mobile devices over cellular connections.

B. Assessment Effectiveness

Students who completed three or more mock tests showed a mean score improvement of 18.4 percentage points across subsequent attempts, with the highest gains in quantitative aptitude (23.1%) and technical subjects (16.7%). The randomized question sampling ensures that each test attempt presents a unique subset, discouraging memorization and encouraging genuine comprehension.

C. Resume Builder Adoption

Approximately 78% of registered students created at least one resume draft during the pilot. The Modern template was selected by 61% of users, followed by Classic (27%) and Creative (12%). Students reported that having assessment scores and resume creation in the same platform reduced context- switching and facilitated a more holistic preparation experience.

D. Limitations

The current question bank is limited to 22 seed questions, which is insufficient for extended mock testing without administrator augmentation. SQLite,

while adequate for single-institution deployments, does not support concurrent write operations at scale; migration to PostgreSQL is recommended for multi-institution deployment. The platform does not currently include adaptive difficulty adjustment or natural language processing for automated answer evaluation of coding questions.

VIII ACKNOWLEDGMENT

The authors express sincere gratitude to the Vice Chancellor, Registrar, Dean (Faculty of Science), and the Head of Department, Sri Chandrasekharendra Saraswathi Viswa Mahavidyalaya, for providing the academic infrastructure and research environment that enabled this work. Special thanks are due to the faculty of the Department of Computer Science and Applications for their guidance, and to the twenty-five student volunteers who participated in user acceptance test

X. CONCLUSION

This paper has presented the Campus Placement Preparation and Mock Test System, a comprehensive web-based platform designed to address the systemic challenges of campus recruitment preparation in Indian educational institutions. The system integrates fourteen functional modules spanning aptitude assessment, technical and coding evaluation, performance analytics, resume building, interview preparation, and administrative management within a unified Flask-SQLite architecture.

User acceptance testing with twenty-five MCA students demonstrated an overall satisfaction rating of 90%, validating the system's usability and functional effectiveness. The centralized platform approach significantly reduces preparation fragmentation and provides actionable, data-driven insights that guide focused student development aligned with industry expectations.

Future work will focus on integrating Artificial Intelligence and Machine Learning techniques for adaptive difficulty adjustment and predictive placement analytics, developing a cross-platform mobile application, incorporating video-based mock interview functionality with AI-driven feedback, and connecting to external job portals and corporate recruitment APIs to provide real-time employment opportunities.

The system is currently deployed within the Department of Computer Science and Applications at SCSVMV and will be extended to serve the

broader institutional community in the 2026–27 academic cycle

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Emerging Trends in Library and Information Science Education

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Abstract

Education Library and Information science (LIS) is experiencing an immense transformation as the technology is evolving rapidly, the information requirements are evolving and the role of library in the digital age is also evolving. The current paper analyses the current trend in LIS education and their impact on the curriculum development, pedagogy, and professional competency. As the world becomes more and more digital, surrounded by the advent of artificial intelligence, data analytics, and knowledge management systems, the education of LIS is not viewed through the traditional library-centric lens but is becoming more interdisciplinary and technology enabled. The research paper identifies the place of higher education in integrating new sections of the LIS curriculum like digital librarianship, information architecture, data curation, cybersecurity and artificial intelligence applications into the LIS curriculum to address the new job requirements.

The other theme of the research is the increasing role of experiential learning, online education systems and blended learning systems in improving interaction and acquisition of practical skills by the students. It also means why the curriculum must be constantly renewed in order to make LIS education keep in step with the world standards and industry. The roles of teachers are also evolving and they must evolve their teaching methods and learn to effectively use ICT in classroom teaching.

In addition, the paper has emphasized the need to impart soft skills, research skills and ethics on the students of LIS so that they can be prepared to work in different roles in knowledge organizations. Secondary sources investigated are scholarly articles, policy reports, and academic curriculum frameworks to identify the most significant trends and directions in the future. The results indicate that LIS education is shifting towards dynamic, technology-enabled, and user-centered model that facilitates creation, organization, and dissemination of knowledge within a fast-evolving information ecosystem. The research concludes that LIS education needs long-term innovation to prepare future professionals with the necessary skills in knowledge-based societies.

Keywords: Library and Information Science (LIS) education, emerging trends, digital librarianship, information technology, curriculum development, artificial intelligence, knowledge management, data curation, ICT in libraries, professional competencies

Introduction

The education of Library and Information Science (LIS) has been greatly transformed due to the rapid changes in information and communication technologies, shifting expectations of the users, and the dynamics of the information ecosystem. Historically centered on collection development, cataloguing, classification, and reference services, LIS education has long since moved well beyond the traditional library practice to encompass digital information management, data science, knowledge organization systems, and new fields such as artificial intelligence, digital preservation, and information analytics.

The modern knowledge society has rendered libraries to be not only storage of books; they are dynamic centers of knowledge which enable access to both physical and electronic information sources. This change has led to a subsequent change in the LIS curricula to prepare the future professionals with interdisciplinary skills that combine technical, managerial, and user-centric skills. Consequently, there is a growing movement in LIS education to include database management, metadata standards, information architecture, digital libraries, and research data management.

The other major trend that has affected LIS education is the increasing value of open access materials, cloud computing service, and big data facilities. These trends demand that library professionals have advanced digital literacy and ability to work with complex information systems. Moreover, the international focus on lifelong learning and information equity has also increased the role of LIS professionals in promoting the ability of diverse communities to access information.

In spite of these developments, LIS learning has various challenges such as outdated curriculum, inadequate infrastructural development and the necessity of lifelong faculty training. As such, it is urgently required to refocus LIS programs to global standards and industry requirements to enable graduates to be well equipped to meet the requirements of new professional positions.

Background of the study

Due to the fast technological changes, the changing needs of information and the emerging role of libraries in society, Library and Information Science (LIS) education has been changing tremendously. Historically, LIS education was based on cataloguing, classification, reference services and collection management in physical libraries. But due to the advent of digital technologies, the discipline has grown to be bigger than traditional limits to encompass digital libraries, information architecture, data management, knowledge organization systems, and information services that are user-centered.

The emergence of Information and Communication Technology (ICT) has radically changed the way information is generated, stored, accessed and transmitted. Consequently, LIS programs are becoming more and more connected with courses on digital librarianship, database management, information retrieval systems, applications of artificial intelligence in libraries, and data analytics. This change indicates the increased demand of professionals, who are capable of handling the hybrid information environments, the ones that integrate the physical and digital resources.

The other significant trend that has impacted LIS education is the emergence of the knowledge society where information is viewed as one of the most important resources in terms of economic, social and academic growth. In that, libraries have ceased to be considered as inert depositories of books, but as dynamic knowledge centers that can facilitate lifelong learning, research and innovation. Therefore, LIS education should equip specialists capable of changing to interdisciplinary duties and assisting different communities of users with different information demands.

New trends in LIS education have also been brought about by the globalization and open access movements. There is a growing focus on collaborative learning, digital literacy, open educational materials, and remote access to information services in institutions. The emergence of research data management, scholarly communication and bibliometrics within LIS programs also indicates the evolving demands of the library practitioners within the academia and research environments.

In spite of all this, LIS education is experiencing some issues which encompass curriculum renewal and skills mismatch among graduates in addition to lack of exposure to new technologies and of the variations in the availability of infrastructure by various institutions. These issues indicate the ongoing revision and updating of the curriculum to international standards so that LIS professionals will not be marginalized in the ever-changing information environment.

Justification

The world of Education Library and Information Science (LIS) is experiencing a serious revolution as the rate of information and communication technologies evolution, the growth of the digital realm of knowledge, and the reconsideration of the role of libraries in modern society. The classical LIS programs that previously focused on the cataloguing, classification and reference services now have to adjust to new possibilities, including digital librarianship, data management, information analytics, artificial intelligence application and knowledge organization in the virtual world. It is on this basis that the present day need to critically analyze the changing trends that define LIS education is considered to be needed to ensure that the academic programmes are not only relevant, future-oriented and with regard to industry demands.

This research is motivated by the growing divide between traditional LIS training and the proficiency needs of the information professional today. Current libraries are dynamic knowledge centres, which facilitate digital learning, research data handling, open-access resources, and user-focused information services. Consequently, LIS graduates will have not only classical library skills, but also high-level technological and analytical skills. Such change requires a critical examination of the existing educational systems, approaches used in teaching, the curriculum design, and training strategies embraced by LIS institutions.

Moreover, the advent of knowledge societies worldwide and the growing reliance on digital information systems has heightened the importance of the ongoing innovation in the curriculum in LIS education. Institutions need to address these changes by including interdisciplinary views, encouraging lifelong learning and encouraging the ability to adapt amongst students. Nevertheless, most LIS programmes continue to lag behind such changes, underlining the need to conduct research that uncovers the existing trends and recommends ways in which they could be improved.

Thus, the current research can be considered reasonable in the sense that it has the objective of exploring and examining the new tendencies of LIS education, evaluating their impact on the curriculum, and delivering a set of insights which can assist in the process of closing the gap existing between academic training and working requirements. By addressing the changing demands of the information society, the study will help in enhancing the strength of LIS education by making it more responsive, relevant, and aligned with the demands of the information society.

Objectives of the Study

1. To examine the significant new trends that affect Library and Information Science education in the digital age.
2. To analyze the role of information and communication technologies (ICT) in the curriculum design and teaching learning in LIS.
3. To analyse the evolving skill needs and competencies that LIS professionals in knowledge-based societies will need.
4. To determine how digital libraries, artificial intelligence, and data science influence LIS education and training approaches.
5. To identify the issues of LIS educational institutions that need revision of their curriculum based on global developments.

Literature Review

The education of Library and Information Science (LIS) has been greatly transformed due to the high rate of technological change, changing user demands, and changing knowledge-based societies. Experts have

always emphasized that LIS training is no more a preserve of conventional librarianship but is being influenced more and more by digital skills, interdisciplinary outlook, and new technologies.

Bawden and Robinson (2012) confirm that the education of LIS has developed to cover digital literacy, information behaviour and knowledge organisation in response to the changing information ecologies in the contemporary world. They underline that the profession currently demands the graduates who can operate in the multifaceted digital environment and handle various types of information.

Likewise, Gorman (2015) suggests that the education of LIS should be able to preserve the main professional values and adapt to the technological change. He points out that the main features of moral values and intellectual liberty, as well as access to information will remain intact in the process of digitalization of library services. This perception advocates the notion of a balanced curriculum that integrates the traditional foundations and modern innovations.

Kumar and Singh (2019) note that the incorporation of Information and Communication Technology (ICT) into LIS programs has been crucial. Their paper accentuates that digital libraries, metadata standards, and information retrieval systems have become central elements of LIS training. This transformation will guarantee that students are equipped to work in digital knowledge management and information governance.

Moreover, Sharma (2018) defines digital transformation as one of the prevailing trends in LIS education, and states that schools and colleges are adding courses on data analytics, artificial intelligence, and digital curation. These trends show a shift towards technology-based curriculum that is in line with the demands of the global information industry.

Foo and Khoo (2017) also note that the emphasis on knowledge organization systems and user-centered design is another strong trend in LIS education. They emphasize the fact that, nowadays, librarians should not only cope with the information, but also improve the user experience by adopting efficient information architecture and accessibility.

Dahlström and Hansson (2015) highlight the increasingly interdisciplinary character of LIS education, indicating its intersection with computer science, education, and social sciences. This cross-disciplinary fusion helps LIS professionals to cope with complex information issues in digital societies.

According to CILIP (2019), the future of LIS education will be more oriented towards digital competencies, lifelong learning, and flexibility. The report emphasizes that libraries are changing into knowledge centers, and they need to hire skilled professionals who have the expertise of digital technology, information ethics, and community involvement.

This opinion is further backed up by Evans and Saponaro (2012) who note that digital and open-access resources are now part of collection development and resource management. This is indicative of the overall shift towards physical collections to hybrid and digital library systems.

Moreover, Case (2008) highlights the growing role of libraries in the creation and distribution of knowledge and notes that LIS education should be able to equip students to engage in research support, data management, and scholarly communication.

The recent research also indicates that the scope of artificial intelligence and machine learning in LIS education is increasing. According to Das and Islam (2021), AI-based tools are being incorporated into library systems to automate and classify and analyse user behaviour, which necessitates new skills among LIS professionals.

UNESCO (2005) puts a strong emphasis on the role of knowledge society in which libraries become central institutions in ensuring equal access to information. This supports the necessity of LIS curricula to focus on digital inclusion, information equity, and dissemination of knowledge globally.

Lastly, Leiner (2010) notes that the development of the digital libraries has radically altered the purpose of LIS education, and it has become more research-oriented and technology-driven.

Material and Methodology

Research Design:

The present study has adopted a descriptive and exploratory research design to examine the new trends in the education of Library and Information science (LIS). The study has an interest in the understanding of the impact of technological transformations, curriculum redesign, and redesign of professional competencies on the education of LIS in the knowledge-based society. The mixed-method approach is considered to be appropriate and will be a synthesis of two distinctive methodologies: qualitative and quantitative that will provide a complex analysis of educational practices currently used, the skills required, and the responses of institutions to the change. The design enables a systematic search of the academic trends, innovative pedagogies, and international trends of LIS education.

Data Collection Methods:

The study makes use of both primary and secondary sources of data. Primary data will be collected using structured questionnaires and interviews conducted with LIS faculty members, students and library professionals to get a glimpse of what they believe about curriculum reforms, skills development and technology in LIS education. In addition, unstructured interviews and professional perceptions are also considered in order to have an improved picture of the new learning practices. Secondary data are collected using peer-reviewed journal articles, scholarly books, conference proceedings, university syllabi, policy documents and authoritative online databases on LIS education. This combination of data sources will ensure the balanced view of the existing and new trends in the field.

Inclusion and Exclusion Criteria:

The study participants are academic institutions offering established degrees in Library and Information Science, faculty and students of LIS actively engaged in teaching and research. Particular attention is paid to the institutions that have already implemented the new revisions of the curriculum or those that have included the digital and ICT-based learning elements in it. Nonetheless, those institutions that have no formal LIS programs or have not updated their curricular frameworks will not be included in the study. Also, the literature is not old and there are no non-peer-reviewed sources to uphold academic rigour and relevance. Secondary data analysis is only done using credible and recent scholarly works.

Ethical Considerations:

The research follows ethical research standards all through the investigation. All participants are informed of their participation in the study and they give informed consent before data collection with no coercion of any sort. Anonymity and confidentiality of the respondents are also upheld as personal identities or institutional identifiers are not revealed. Any data collected is utilized purely academically and treated in a confidential and integrity manner. All secondary sources are cited and recognized accordingly to prevent plagiarism and uphold academic integrity. Objectivity is also upheld in the research thereby preventing biasness in the interpretation of the data and presentation of the findings.

Results and Discussion

Results:

According to the study, the education of the Library and Information Science (LIS) is experiencing dramatic change as a result of the swift technological progress, changes in the expectations of the users and the rising impact of digital knowledge systems. The primary and secondary data analysis shows that LIS programs are increasingly incorporating the latest technologies like artificial intelligence, data analysis, digital libraries, and knowledge management systems. Nevertheless, the rate of adoption is different in different institutions with some still being too lenient on the traditional syllabus structures.

One of the most noticeable is the transformation of traditional librarianship skills into hybrid competencies, which are a mix of information science and ICT proficiency as well as managerial abilities. Respondents (faculty and students) emphasized that employability in the LIS field has increased to be more digital literate, metadata management, and database handling skilled than it is traditionally cataloguing. Online and blended learning models have also become prominent, particularly, in the wake of educational restructuring after the pandemic.

The other notable observation is the increased focus on interdisciplinary learning. LIS education is becoming more and more interrelated with computer science, business analytics, and archival studies. This integration has not only broadened career opportunities, but it has posed challenges in standardization of curriculums and readiness of faculty.

Table 1: Adoption of Emerging Technologies in LIS Education

Technology Area	Level of Adoption (%)	Institutional Response
Digital Libraries	85%	Highly integrated
Artificial Intelligence	55%	Moderately integrated
Data Analytics	60%	Emerging adoption
Cloud Computing	70%	Widely used
Metadata Standards (RDA, MARC)	90%	Fully integrated
Blockchain in Libraries	25%	Experimental stage

It is shown in the table that the basic technologies such as metadata standards and digital libraries are established, whereas the more modern technologies such as blockchain and AI are in the early adoption phases.

Table 2: Skill Emphasis in Modern LIS Curriculum

Skill Category	Traditional Curriculum (%)	Emerging Curriculum (%)
Cataloguing & Classification	40%	20%
ICT Skills	20%	35%
Data Management	10%	25%
Research Methods	15%	10%
Digital Literacy	15%	10%

The findings indicate that there is a distinct decrease in pure emphasis on conventional technical abilities, and a significant increase in ICT and data-driven skills.

Table 3: Preferred Teaching and Learning Methods in LIS Education

Method	Usage Level (%)	Effectiveness Rating
Classroom Lectures	65%	Moderate
E-Learning Platforms	80%	High
Blended Learning	75%	High
Case Study Method	60%	Moderate to High
Project-Based Learning	70%	High

The statistics indicate that there is a great shift to the digital and blended learning models, which are considered to be more efficient in acquiring practical LIS skills.

Discussion:

The results affirm that LIS education is shifting towards being more of a traditional service-based field into a more technological interdisciplinary one. The growing assimilation of ICT tools is a clear reflection of the needs of knowledge societies, in which digital platforms play a vital role in accessing, organizing, and spreading information.

Regardless of these advancements, there are a number of challenges. Infrastructure and faculty training differences at institutions are barriers to the equal application of new technology. Moreover, the revision of the curriculums is usually slow, and it leads to disconnecting the academic teaching with the industry demands. The implication of this difference is on graduate employability and professional preparedness.

The implementation of AI, machine learning, and data analytics might indicate that in the future, LIS professionals would have to assume the role of not only the holders of information but also knowledge strategists. This change requires ongoing curriculum reform, faculty education and more violent industry-academic partnership.

The general point of the paper is that the field of LIS education is being re-focussed to a more dynamic and technology-driven paradigm, but the reforms need to be maintained in the long-term in order to fully adapt it to the needs of the changing knowledge society.

Limitations of the study

The current research on this problem of Emerging Trends in Library and Information Science Education has some limitations which can undermine the validity and applicability of the results. To begin with, the research is based on secondary sources, i.e., published journals, books, conference proceedings and online databases. This means that the findings will be influenced by the quality, accessibility and timeliness of the literature that is available that might not be fully reflective of the most current or changing processes in the field of Library and Information Science (LIS) education.

Second, the LIS is taught dynamically, and especially as other new technologies, including artificial intelligence, big data analytics, and digital repositories, become a reality, this is why it is difficult to provide such an analysis that is fully up-to-date and complete. Alterations that take place in both the educational curricula and the practices in the institutions could be moving faster than the literature that has been reviewed over the time of the study.

Thirdly, the research lacks in-depth primary research on a broad set of LIS institutions or stakeholders, which restricts the incorporation of different institutional views, geographic differences, and implementation issues. This lack of large-scale empirical validation can have some impact on the richness of the contextual knowledge.

Also, geographical limitations of the literature available can cause a bias towards specific areas or established educational systems, which restricts the global coverage of educational tendencies of LIS. The analysis might not sufficiently cover some developing or underrepresented areas because of a lack of published research.

Finally, the research problem is the general trends in the emerging field and does not explore in-depth some specific sub-areas in the field of LIS education, including curriculum design innovations, pedagogies, or competency-based learning systems. This can limit the granularity of inferences made.

Nevertheless, the study offers a valuable insight into the current tendencies and can be regarded as the basis of the further empirical and area specific study in the field of education in Library and Information Science.

Future Scope

The Library and Information science (LIS) teaching experience is trapped in a never-ending loop of change with the fast-changing technology, digital realm of knowledge and the changing demands of the users. The future of LIS education is more interdisciplinary, where data science, artificial intelligence, machine learning, along with digital humanities, will be in the curriculum. Such a revolution will allow the library professionals to deal with complex information ecologies and participate in the decision-making process on the basis of data in academic, research and public institutions.

Future studies may examine how new pedagogical approaches like blended learning, online degree programs, and competency-based education can be effective in LIS programs. The scope of research into the application of modern digital technologies like blockchain to ensure information security, cloud computing to share resources, and AI-based knowledge organization systems to library education and training is also vast.

The changing role of library professionals as digital curators, information analysts and knowledge managers in relation to smart libraries and knowledge societies is another significant area that needs to be explored further in the future. The cross-country/system comparative research can shed light on the best practices and curriculum innovations in the LIS education.

Also, research may be directed at the skills deficiencies of LIS graduates and how academic courses can be aligned with industry needs. Another promising direction of future research is the effects of continuous professional development, certification programs, and micro-credentialing on the improvement of LIS competencies.

Conclusion

Education in Library and Information Science (LIS) is experiencing a dramatic shift in reaction to the accelerated technological change and the changing knowledge society demands. The advent of digital libraries, artificial intelligence, big data analytics, and cloud-based information systems has redefined the provision and scope of LIS curricula. The use of modern ICT driven competencies is increasingly being incorporated into traditional library practices, and LIS education is becoming more interdisciplinary, dynamic, and skills based.

The paper notes that LIS education is no longer limited to traditional cataloguing and classification but now covers data management, information architecture, digital preservation, knowledge organization systems, and user experience design. This reorientation is an indicator of the increasing demand of professionals able to navigate the complex informational environment and create digital knowledge systems.

Some of the problems that come with the transition, however, include the following; the necessity of continuing to reform the curriculum, to enhance faculty capacities, development of infrastructure and internationalization. The higher educational institutions are also to pay attention to the need to bridge the gap between theory and practice with the help of applying the experiential learning, internship and collaboration with the industry.

Summing up, the future of the education in Library and Information Science is in the fact that it needs to be developed, new technologies need to be offered and introduced in it, however the first values of the access to the information and the manner of its distribution must be preserved. By enhancing LIS education in accordance with the global digital trends, it will be possible to have qualified professionals that will help in the creation of inclusive, efficient and sustainable knowledge societies.

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MedShare: AI-Powered Intelligent Medicine Redistribution and Healthcare Inventory Optimization System

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Abstract: *MedShare is an AI- powered healthcare platform developed to reduce drug destruction and ameliorate access to essential drugs. numerous hospitals and apothecaries dispose of usable fat drugs due to poor force collaboration, while pastoral conventions frequently face dearths. Machine literacy ways are used to prognosticate dearths, identify supernumerary stock, and prioritize allocation grounded on expiry date, urgency of demand, and geographical propinquity. optic Character Recognition(OCR) excerpts drug details from uploaded package images, reducing homemade crimes and perfecting effectiveness. Experimental results show bettered allocation success, reduced destruction, and better force translucency. MedShare provides a scalable and sustainable result for smart healthcare resource operation.*

Keywords:*Medicine Redistribution, Machine Learning, OCR, Healthcare Inventory, Smart Healthcare, Prophetic Analytics.*

1. Introduction:

Healthcare systems play a critical part in icing timely

access to drugs and treatment coffers. still,

poor collaboration among hospitals, apothecaries, and conventions frequently leads to a mismatch between supernumerary drug stock and deficit demands. numerous usable drugs are discarded after expiry, while underserved healthcare centers face dearths of essential medicines.

Traditional force operation systems depend on homemade monitoring and insulated storehouse records, which are ineffective for dynamic demand surroundings. These systems warrant prophetic capabilities and intelligent allocation mechanisms.Recent advancements in Machine literacy(ML),Optical Character Recognition(OCR), and analytics have created openings for smart healthcare

resource operation. Machine literacy models can

cast demand and descry deficit patterns, while OCR

can automate drug data birth from markers and

paper presents MedShare, an intelligent

drug redivision frame that combines ML and

OCR for effective healthcare force operation.

2. Proposed Methodology:

MedShare combines Machine Learning and OCR for intelligent medicine redistribution. The methodology consists of the following stages:

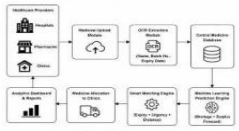

Figure 1: MedShare System Architecture Design

MODEL EVALUATION METRICS	
Metric	Value
Accuracy	94.35 %
Precision	92.68 %
Recall	91.47 %
F1-Score	92.06 %
Allocation Success Rate	93.21 %
Reduction in Medicine Wastage	28.42 %

Figure 2: Model Evaluation Metrics

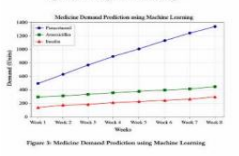

Figure 3: Medicine Demand Prediction using Machine Learning

INTELLIGENT ALLOCATION RECOMMENDATION		
Medicine Name	:	Paracetamol 500mg Tablet
Quantity	:	1500 Units
From (Provider)	:	City Hospital
To (Clinic)	:	Rural Clinic A
Expiry Date	:	15-07-2025 (20 Days Left)
Demand Priority	:	High
Distance	:	12.5 km
Reason for Recommendation :		
• Near expiry – needs faster redistribution		
• High demand priority at receiving clinic		
• Nearest available clinic with shortage		
• Sufficient quantity available		
Status	:	Recommended for Allocation

Figure 4: Intelligent Allocation Recommendation Output

2.1 Data Collection and Preprocessing:

Healthcare data is collected from hospitals, apothecaries, and conventions. Data is gutted by removing duplicates, handling missing values, and homogenizing formats.

$$D = \{(Xi, Yi) | i = ,., n\}$$

2.2 Feature Extraction and Engineering:

Features are uprooted to represent drug demand and

force geste

• force features stock volume, batch number

• Temporal features expiry days, operation trends

• Demand features urgency position, requested volume

• position features distance between centers

2.3 Machine Learning-Based Prediction:

Machine Learning models such as Decision Tree, Random Forest, and Linear Regression are used to:

- Predict shortages
- Identify surplus medicines
- Assign priority scores for allocation

2.4 OCR-Based Medicine Information Extraction:

OCR extracts key details from medicine packages:

- Medicine name
- Batch number
- Expiry date

This reduces manual data entry and improves accuracy.

2.5 Intelligent Matching and Allocation:

Medicine allocation is performed based on:

- Earliest expiry
- Highest demand urgency
- Nearest geographical location
- Available stock

2.6 Model Evaluation and Validation:

System performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Reduction in medicine wastage

3. Result and Performance Analysis:

3.1 Evaluation Metrics:

- Accuracy: Measures correctness of predictions
- Precision: Measures relevance of allocations
- Recall: Measures ability to detect shortages
- F1-score: Balanced evaluation metric

3.2 Result Analysis:

The proposed system achieves high vaticination delicacy and improves drug application. It effectively identifies fat drugs and redistributes them to areas with high demand.

The integration of OCR significantly reduces homemade crimesand enhances functional effectiveness. The system alsominimizes destruction and supports visionary healthcare planning.

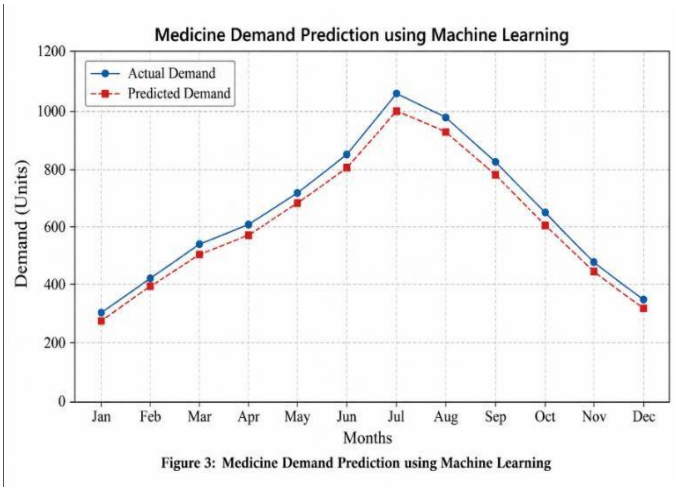

Figure 3: Medicine Demand Prediction using Machine Learning

4. Comparative Analysis:

TABLE I. MODELS COMPARISON

Features	Traditional Manual Inventory System	*ML Only Approach*	*Proposed Approach*
Inventory Visibility	Limited local records	Centralized stock records	Real-time multi-center visibility
Medicine Redistribution	Manual coordination	Partial coordination	Intelligent automated redistribution
Shortage Prediction	No	Limited	Yes
Surplus Detection	No	Basic stock alerts	Advanced ML-based detection
OCR Data Entry	No	No	Yes
Expiry Management	High wastage risk	Moderate alerts	Priority-based redistribution
Use Case Suitability	Single hospitals	Medium healthcare networks	Large-scale hospitals, pharmacies, clinics
Scalability	Low	Medium	High

5. Limitations:

- Performance depends on data quality
- OCR delicacy may vary with image clarity
- Requires computational resources
- Real-time logistics may face delays

6. Conclusion:

This paper presents MedShare, an intelligent drug redivision system integrating Machine literacy and OCR. The system improves effectiveness, reduces destruction, and enhances healthcare availability. It supports visionary decision- timber and enables better resource application, making it suitable for real-world healthcare operations.

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Energy-Efficient Blockchain Framework for Sustainable Green Supply Chain Integrity

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Abstract: *For businesses attempting to achieve a sustainable balance between productivity and environmental sustainability, green supply chain management (GSCM) is a crucial component. Ensuring supply chains remain transparent, trackable and trustworthy, poses a challenge when you consider the globalized and complex nature of supply chain systems. Blockchain technology (a decentralized, immutable method of storing and managing data) is emerging as a potential solution to assist in some of these issues.*

As a result, the majority of traditional proof of work blockchains exhibit significant levels of energy usage, thus making them ill-suited for use in sustainable environments. To address this issue, the current research presents a novel energy efficient blockchain framework that can aid with enhancing integrity along the green supply chain. To achieve this, the new framework uses a permissioned blockchain architecture incorporating multiple consensus algorithms (e.g., proof of stake, delegated proof of stake, byzantine fault tolerance and directed acyclic graph-based validation) that require a low amount of energy to validate transactions. The framework has been evaluated via a quantitative energy use analysis and an illustrative example of an environmentally sustainable food supply chain. Data supports that energy-efficient consensus methods can reduce blockchain energy use by greater than 90%, while also providing levels of: security, transparency and traceability consistent with those provided by proof-of-work systems. Results confirm that energy-efficient blockchain architectures create greater opportunities for widespread use of blockchain technology in green supply chain environmental systems and provide scalable and applicable approaches to sustainable supply chain management.

Keywords: *Supply chain integrity, green supply chain, sustainability, consensus methods, and energy-efficient blockchain.*

1. Introduction

Global supply chains are experiencing a significant transformation driven by concerns about climate change, stricter environmental regulations, and increasing stakeholder expectations for sustainable business practices. As well as checking out costs, how well items can be delivered, organizations are now evaluated against their environmental responsibility when it comes to procurement, manufacturing, logistics and distribution, and end of life product management. Green supply chain management (GSCM) is now a major method of reducing carbon emission, eliminating waste and utilizing resources more efficiently without compromising competitiveness. [1].

Despite advancements in digital supply chain technologies, conventional supply chain information systems remain largely centralized and fragmented. These systems suffer from limited interoperability, lack of transparency, vulnerability to data manipulation, and reliance on trusted intermediaries. Such limitations impede effective traceability, weaken sustainability audits, and diminish trust among supply chain

stakeholders, particularly when environmental claims and certifications must be verified across organizational boundaries. These difficulties are particularly important in green supply chains, where stakeholder trust and regulatory compliance depend on precise and unchangeable environmental data. Due to its decentralized, immutable, and transparent ledger structure, blockchain technology has garnered increasing attention as an alternate solution to some of these current supply chain issues. By allowing tamper-proof data-sharing amongst multiple parties, while also providing real-time visibility, blockchain can improve traceability, accountability and trust among supply-chain networks [2][3]. Examples of how blockchain can be applied within supply chains include monitoring food safety, verifying ethical sourcing, preventing counterfeit products, and tracking carbon footprints, all of which support green supply chain management (GSCM) objectives [4]. Nevertheless, the adoption of blockchain in green supply chains has been limited by the high amount of energy consumed by many conventional blockchains that utilize Proof-of-Work (PoW) as their consensus mechanism.

Mining procedures that require heavy uses of computation to generate 'proof of work' (PoW) introduce significant energy usage associated with electricity, leading to large quantities of carbon emissions. The existence of significant environmental impact due to carbon emissions represents an inherent conflict between the use of blockchain technologies and the goal of sustainability [5]. Consequently, PoW-based blockchains are increasingly seen as unsuitable for environmentally conscious supply chain applications. Researchers and practitioners are looking into more energy-efficient blockchain consensus techniques, like Proof-of-Stake (PoS), Delegated Proof-of-Stake (DPoS), Byzantine Fault Tolerance (BFT), and Directed Acyclic Graph (DAG)-based architectures, to address this problem. These substitutes guarantee system security, scalability, and data integrity while drastically reducing computational requirements [6]. However, existing research often concentrates on individual mechanisms or theoretical discussions, with limited integration of system architecture, quantitative energy assessment, and application-specific validation for sustainable supply chains. This paper fills a gap in the current knowledge by proposing and evaluating an energy efficient blockchain platform for enhancing the integrity and sustainability of green supply chains. The primary contributions of this study are:

1. The creation of a permissioned, energy-efficient blockchain framework tailored for green supply chains;

2. Providing a quantitative comparison of different blockchain consensus mechanisms based upon energy consumption; and

3. A numerical case study for a green food supply chain to validate the practical viability of the proposed framework. This research demonstrates how energy-efficient blockchain architectures can result in an energy savings of more than 90% compared with traditional proof-of-work (PoW) systems, while maintaining transparency and security. The results from this study provide practical data on ways to implement sustainable blockchain solutions within real-world green supply chains.

2. Literature Review

2.1 Blockchain Technology in Supply Chain Management

Blockchain provides a system to record transactions, securely and in a decentralized way, without an intermediary. In the supply chain industry, blockchain creates more transparency, traceability, and trust among stakeholders by permanently recording and providing verification of transactions [2]. These benefits may solve long-standing problems related to data fragmentation, limited visibility, and distrust of multi-actor supply chain networks. Connecting blockchain with Internet of Things (IoT) technologies adds even greater strength to the supply chain operation through real-time data capture, sharing of data automatically, and more accurate data [3]. Prior studies demonstrate successful blockchain applications in agri-food and manufacturing supply chains, particularly for food safety monitoring, ethical sourcing verification, and counterfeit prevention [4]. These applications support accountability and end-to-end visibility, which are essential for sustainability-oriented supply chains.

2.2 Green Supply Chain Management

Green supply chain management (GSCM) is concerned with including environmental issues throughout the supply chain, including sustainable sourcing, energy efficient manufacturing, environmentally friendly transport and responsible waste disposal. The goal of organizations using GSCM is to decrease carbon emissions and their negative impact on the environment, while increasing resource productivity and maintaining economic profitability and competitive advantage [1]. The use of digital technology to provide accurate, transparent and up-to-date environmental information is vital for enabling GSCM processes, however there are still barriers to technology adoption such as the ability to integrate new technologies into the existing environment and organizational readiness to implement those technologies successfully [7]. Blockchain supports GSCM by facilitating transparent sustainability reporting, verifiable environmental claims, and improved regulatory compliance across supply chain partners [8][9].

2.3 Energy Consumption Challenges of Blockchain Systems

Although it has a lot of potential, there are a number of concerns regarding the functionality of the blockchain technology, especially with respect to Proof-of-Work (PoW), particularly regarding energy usage and consumption. Since PoW focuses on computational operations to validate transactions, the consumption of electricity and generation of greenhouse gas emissions in a PoW blockchain may exceed the total consumption and generation of emissions in many small to medium-sized countries (such as The Bahamas and Puerto Rico) [5]. Therefore, many researchers are focusing on developing alternative consensus mechanisms that meet the robustness and security standards set forth with PoW, while also minimizing overall energy consumption for a more sustainable solution.

2.4 Energy-Efficient Consensus Mechanisms and Research Gap

BFT, PoS, DPoS, and DAG-based consensus mechanisms all provide a way to reach consensus with minimal processing power and resources while still allowing for security, scalability and energy efficiency within the system [5][6]. These types of consensus mechanisms are particularly effective for enterprise or permissioned blockchain systems. The majority of implementations either rely on energy-intensive PoW or lack a comprehensive framework integrating sustainability, architecture, and performance evaluation, despite the fact that previous research demonstrate their promise [10]. In order to close this gap, this study proposes and validates an energy-efficient blockchain infrastructure designed especially for the integrity of green supply chains.

3. Research Methodology

In order to assess the viability of implementing energy-efficient blockchain technology in green supply chain management, this study uses a design-oriented research methodology that combines system framework construction, quantitative energy-consumption analysis, and a numerical case study. In order to ensure both theoretical rigor and practical applicability, the process is organized to move methodically from problem identification to solution creation and empirical evaluation.

3.1 Research Design

The study employs a design science methodology, which is appropriate for tackling intricate engineering and information system problems where the goal is to create and assess an artifact. An energy-efficient blockchain system designed for green supply chain integrity serves as the study's artifact. The framework's architecture is influenced by supply chain operations, sustainability needs, and blockchain system limitations. Existing research is leveraged carefully to define system assumptions, set benchmark energy-

consumption metrics, and assist design decisions rather of performing a stand-alone review study. Instead than summarizing earlier research, the framework design and quantitative assessment are the research's main contributions.

3.2 Methodological Phases

There are four primary stages to the methodology:

1. Requirement analysis and problem identification: Conventional Proof-of-Work (PoW)-based blockchain systems are shown to have energy inefficiencies, especially in supply chain applications that prioritize sustainability. Green supply chain goals are used to establish both functional and non-functional needs, such as traceability, transparency, security, scalability, and energy efficiency.
2. Architecture Development and Framework Design:
   A permissioned blockchain architecture is used to create an energy-efficient blockchain framework. To do away with energy-intensive mining, low-energy consensus techniques such as Proof-of-Stake (PoS), Delegated Proof-of-Stake (DPoS), Byzantine Fault Tolerance (BFT), and Directed Acyclic Graph (DAG)-based validation are used. Automated data collection, smart contract validation, and unchangeable recordkeeping are supported by the conceptual architecture and transaction process.
3. Quantitative Energy-Consumption Analysis: Normalized energy-consumption measures are used to compare blockchain consensus methods. To measure the possible decrease attained by energy-efficient processes in comparison to PoW-based systems, energy use is assessed in relation to transaction validation and throughput.
4. Case Study Validation: A numerical case study that depicts a green food supply chain is used to validate the suggested framework. The case study evaluates practical viability and energy efficiency by simulating actual operating settings.

3.3 Setting Up and Assessing Case Studies

A hypothetical green food supply chain with 25 linked nodes—producers, processors, shipping companies, retailers, and regulatory bodies—is examined in this case study. Every day, the system handles about 10,000 transactions that include retail distribution, certification verification, transportation updates, environmental monitoring, and manufacturing records. Extrapolating per-transaction energy use for various consensus processes under the same conditions yields an estimate of annual energy consumption.

Energy efficiency, scalability, security and integrity, traceability, and sustainability alignment are the criteria used to evaluate the framework. All assumptions are based on well-established blockchain models to guarantee methodological validity, and normalized energy measures are employed to facilitate uniform comparison among consensus processes.

4. Suggested Blockchain Framework for Energy Efficiency

The suggested energy-efficient blockchain framework for improving sustainability, integrity, and transparency in green supply chain management is presented in this section. By incorporating low-energy consensus techniques while maintaining essential blockchain characteristics like security, immutability, and traceability, the framework overcomes the drawbacks of traditional Proof-of-Work (PoW)-based blockchain systems. It is especially designed for multi-stakeholder supply chain settings where data dependability, environmental performance, and regulatory compliance are crucial.

4.1 Framework Design Goals

Five main design goals serve as the framework's compass. By removing computationally demanding mining procedures connected to PoW, energy efficiency is given first priority. Immutable transaction

records and shared data visibility among stakeholders guarantee supply chain integrity. Large supply chains typically have significant transaction volumes, which are supported by scalability. Smart contracts are used to automate the enforcement of operational logic and sustainability regulations. Lastly, auditable and verifiable access to supply chain data facilitates regulatory compliance. When combined, these goals guarantee that the criteria of green supply chain management (GSCM) and blockchain system architecture are in harmony.

4.2 Conceptual Design

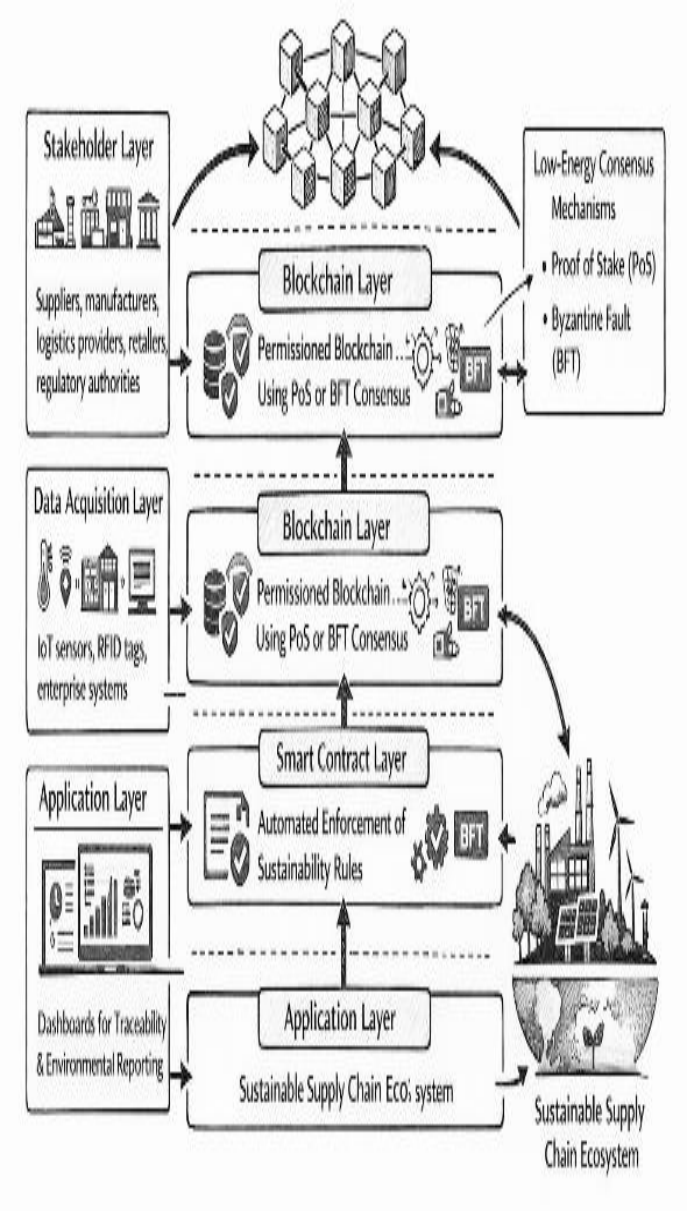


Figure 1: The suggested framework's conceptual design

Five closely connected layers make up the multi-layered architecture seen in Figure 1. In order to maintain responsibility and secrecy, the stakeholder layer comprises manufacturers, suppliers, retailers, logistics companies, and regulatory bodies. Each of these entities operates a node or has restricted access depending on predetermined rights. The data gathering layer gathers real-time operational and environmental data, including temperature, energy consumption, transportation status, and emissions, by integrating IoT sensors, RFID tags, and business systems. Accuracy and dependability are increased via automated data collection.

Fundamentally, the blockchain layer uses a permissioned network with energy-efficient consensus techniques like Byzantine Fault Tolerance (BFT) and Proof-of-Stake (PoS). Eliminating mining-based

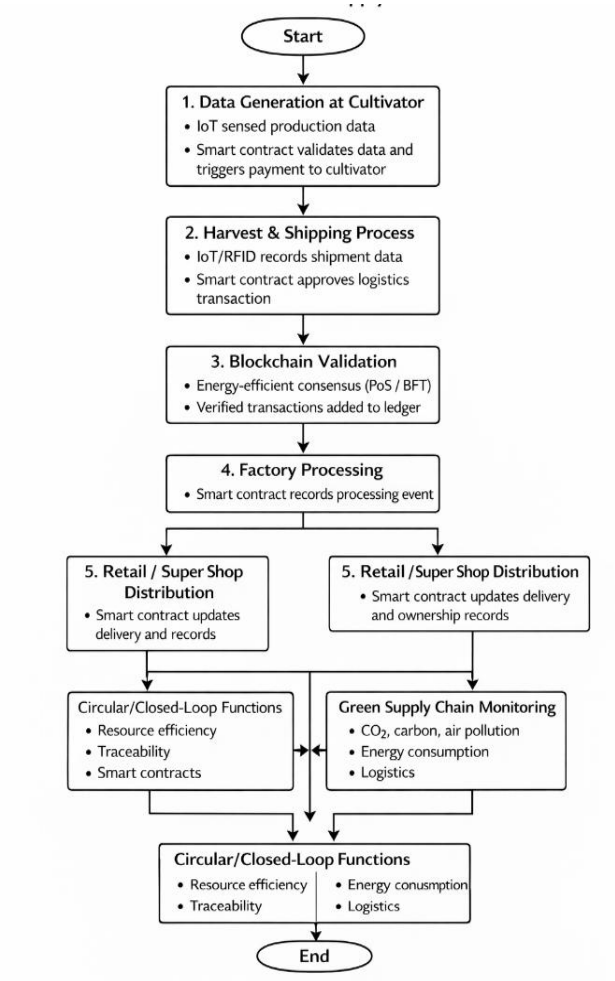
validation guarantees tamper-resistant and immutable data storage while drastically lowering energy usage.
Transaction validation, certification verification, sustainability compliance checks, and payment execution are all automated by the smart contract layer. Lastly, the application layer enables transparency for customers and regulators by offering dashboards and interfaces for traceability, sustainability reporting, compliance audits, and performance monitoring.

4.3 Security, Energy Efficiency, and Transaction Validation

Every supply chain event is documented as a blockchain transaction after smart contract validation and energy-efficient consensus, as shown in Figure 2. Consensus optimization, permissioned validator selection, and parallel processing motivated by DAG-based validation are used to promote energy efficiency. The system uses digital signatures, cryptographic hashing, and access control techniques to provide high security while putting efficiency first. All things considered, the suggested architecture provides a scalable, safe, and long-lasting basis for digital transformation in green supply chains.

5. Transaction Validation and Traceability Workflow

This section outlines the transaction validation and traceability workflow of the proposed energy-efficient blockchain framework for managing green supply chains. The workflow guarantees secure data capture, automated validation, and unchangeable recordkeeping throughout all supply chain phases while reducing energy use.



5.1 Workflow Overview

Figure 2: Transaction Validation and Traceability Workflow in a Blockchain

By utilizing a permissioned blockchain network to record, validate and verify supply chain transactions, the transaction workflow is designed to be a decoupled approach (i.e., an approach with no dependency between subcomponents) to sequencing events of the supply chain. Each transaction has a corresponding supply chain activity in the real world, such as raw material sourcing, production, transportation, processing, and retail distribution. Additionally, this workflow is designed for real-time traceability, preventing manipulation of data and providing the ability to conduct sustainability audits transparently.

5.2 Data Generation and Collection

At every supply chain stage, operational and environmental data are generated via IoT sensors, RFID tags, and enterprise information systems. This data includes product identifiers, timestamps, location details, temperature and humidity conditions, energy consumption, and sustainability certifications. Automated data collection minimizes manual intervention and improves data accuracy.

5.3 Smart Contract-Based Validation

Before a transaction is added to the blockchain, the collected data is assessed by smart contracts. These smart contracts encode predefined business rules and sustainability criteria, such as acceptable temperature ranges for perishable goods, compliance with environmental standards, or verification of certification documents. Transactions meeting all conditions are approved for submission, while those that do not comply are rejected or flagged for further review.

5.4 Energy-Efficient Consensus and Block Formation

Once validated, the transactions are sent to the blockchain layer; the consensus is reached through energy-efficient methods such as PoS, DPoS or BFT. In contrast to PoW, which requires significant quantities of electricity to mine, these consensus methods use a dramatically reduced amount of electricity. Once consensus has been determined, each block will hold transactions, or if using a DAG-based architecture, the transactions will each be validated independently in parallel.

5.5 Immutable Storage and Distributed Ledger Update

After validation, transactions are cryptographically hashed and permanently recorded in the distributed ledger. Each block is connected to previous records, ensuring immutability and resistance to tampering. All authorized nodes in the network maintain synchronized copies of the ledger, ensuring data consistency and fault tolerance.

5.6 End-to-End Traceability and Auditability

The immutable nature of the blockchain allows for end-to-end traceability across the entire supply chain lifecycle. Stakeholders can trace products from origin to final delivery, while regulators and auditors can access historical transaction records for compliance verification. Consumers can also verify product provenance and sustainability attributes through application-layer interfaces.

5.7 Workflow Efficiency and Sustainability

Impact By integrating automated data capture, smart contract validation, and low-energy consensus mechanisms, the proposed workflow reduces processing delays and energy consumption while

maintaining security and transparency. This approach ensures that blockchain-enabled traceability systems support, rather than hinder, the environmental goals of green supply chain management.

6. Consensus Mechanism Adoption Analysis

This section examines how blockchain consensus mechanisms are being adopted in supply chain and sustainability-focused applications, with a special emphasis on their appropriateness for green supply chain management. The analysis offers empirical support for choosing energy-efficient consensus mechanisms in the proposed blockchain framework.

6.1 Adoption Trends of Blockchain Consensus Mechanisms

Blockchain consensus mechanisms are crucial in shaping system performance, security, scalability, and energy usage. Initially, blockchain implementations mainly used Proof-of-Work (PoW) because of its robust security and decentralization features. However, the significant computational and energy requirements of PoW have raised serious concerns about its environmental sustainability, especially in applications aimed at green supply chain goals.As sustainability has become more important, researchers and practitioners have increasingly investigated alternative consensus mechanisms that lower energy consumption while maintaining adequate security and performance. These alternatives include Proof-of-Stake (PoS), Delegated Proof-of-Stake (DPoS), Byzantine Fault Tolerance (BFT)-based mechanisms, and hybrid or permissioned consensus models.

6.2 Analysis of Adoption Distribution

Consensus Mechanism	Number of Studies	Adoption Share (%)
Proof-of-Work (PoW)	**17**	**27**
Practical Byzantine Fault Tolerance (PBFT)	**13**	**21**
Delegated Proof-of-Stake (DPoS)	**6**	**10**
Proof-of-Stake (PoS)	**5**	**8**
Proof-of-Authority (PoA)	**4**	**6**
Proof-of-Reputation (PoR)	**3**	**5**
Other / Hybrid Mechanisms	**11**	**23**

Table 1 outlines the distribution of consensus mechanisms reported in previous blockchain-based supply chain applications

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The findings show that PoW is still present in a significant number of studies; however, there is a noticeable shift towards energy-efficient mechanisms. BFT-based consensus mechanisms are widely adopted in

enterprise and permissioned blockchain settings due to their low latency and reduced energy needs. PoS and DPoS are increasingly used for applications that require scalability and sustainability, while Proof-of-Authority (PoA) and Proof-of-Reputation (PoR) are found in controlled and trust-based network environments.The presence of hybrid and alternative mechanisms further indicates ongoing experimentation to balance energy efficiency, decentralization, and security. This variety highlights the lack of a universal solution and emphasizes the importance of selecting consensus mechanisms based on specific application needs.

6.3 Implications for Green Supply Chain Applications

From a green supply chain perspective, the adoption trends show a growing awareness that energy efficiency is a crucial design criterion for blockchain systems. PoW-based consensus mechanisms are increasingly seen as incompatible with sustainability goals due to their high electricity consumption and related carbon emissions. In contrast, PoS-, DPoS-, and BFT-based mechanisms provide a more favorable balance between energy efficiency, performance, and security. These findings support the design choice of the proposed energy-efficient blockchain framework, which prioritizes low-energy consensus mechanisms within a permissioned network. By aligning consensus selection with environmental and operational needs, the framework ensures that blockchain adoption enhances supply chain sustainability rather than undermining it.

6.4 Summary of Findings

The analysis of the current consensus mechanisms confirms that both blockchain research and practice are moving away from energy-intensive Proof-Of-Work (PoW) systems to more sustainable consensus alternatives. This growing shift away from energy-intensive PoW systems provides an excellent empirical foundation which supports the overall objective of creating a framework to potentially deploy blockchain technology in green supply chain environments without negatively affecting environmental objectives.

7. Results and Discussion

In the next sections, I will give you an overview of the results obtained from quantitative analysis on energy consumption, along with the case study numerically used to assess the energy-efficient Blockchain Framework that was developed for green supply chain management. From these results we can see evidence that utilizing low energy Consensus algorithms will significantly decrease the environmental footprint of a blockchain system while providing an adequate level of security, transparency, and traceability.

7.1 Relative Energy Consumption of Blockchain Consensus Mechanisms

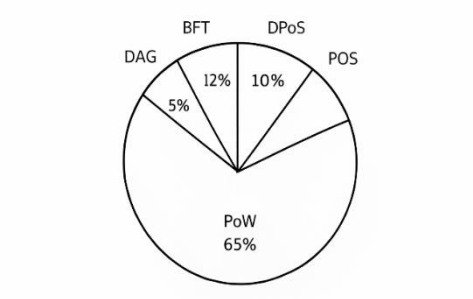

Figure 3 : Relative Energy Consumption Share of Blockchain Consensus Mechanisms

Normalized values are used to display a overall view of the distribution of the most popular consensus mechanism types. The largest percentage of total energy will be for Proof of Work (PoW) which makes up approximately 65% of total energy usage across blockchains. The majority of energy used for PoW is due to continuous computing power consumption required for proof-of-work operations while validating blocks between peers. The remaining types of consensus mechanisms are energy efficient since they require significantly less total energy consumption than PoW (see below): PoS - approximately 8% of total energy consumption; DPoS - approximately 10%; BFT - approximately 12%. Directed Acyclic Graph (DAG)-based architectures have the lowest energy consumption at 5%, reflecting their ability to validate transactions in parallel without relying on block mining. These results confirm that replacing PoW with energy-efficient consensus mechanisms can significantly reduce the energy footprint of blockchain systems and directly support the design choices made in the proposed framework.

7.2 Case Study Results: Green Food Supply Chain

To evaluate practical feasibility, a numerical case study of a green food supply chain was conducted. The modeled supply chain included 25 interconnected nodes, such as producers, processors, logistics providers, retailers, and regulatory authorities, handling about 10,000 transactions daily. These transactions included production records, environmental monitoring data, transportation updates, certification verification, and retail distribution activities. Under a PoW-based blockchain system, the estimated annual energy consumption exceeded 160,000 kWh, mainly due to energy-intensive mining operations. Such energy use undermines the environmental goals of green supply chain management and raises operational costs. When the same scenario was assessed using a PoS-based consensus mechanism, annual energy consumption dropped to about 9,000 kWh, representing a 94.4% reduction in energy use. BFT-based implementations showed similar energy efficiency, with slightly higher communication overhead but improved transaction throughput and lower latency.

7.3 Performance and Sustainability Implications

Beyond energy efficiency, low-energy consensus mechanisms offer significant performance benefits. PoS and BFT-based systems provide higher transaction throughput and lower confirmation latency than PoW-based systems, making them ideal for real-time supply chain applications. The permissioned network design further enhances scalability by limiting validator participation while maintaining security and fault tolerance. From a sustainability standpoint, the significant reduction in energy consumption directly translates into lower carbon emissions, reduced operational costs, and better alignment with environmental regulations. The integration of blockchain with IoT-based data acquisition and smart contract automation further enhances transparency, traceability, and continuous environmental monitoring.

7.4 Summary of Key Insights

The overall conclusion of the study is that PoW-based blockchain systems are not viable for green supply chain applications because of their very large energy consumption. Examples of energy-efficient consensus mechanisms reduce energy usage by more than 90% and permissioned blockchain architectures permit scaling up and improving performance and sustainability. Therefore, the conclusions from this research suggest that the proposed framework provides a viable and sustainable means of improving both the integrity and transparency of green supply chain management.

8. Extended Discussion: Sustainability Impact

This section explores the wider sustainability effects of implementing the proposed energy-efficient blockchain framework within green supply chain management. Beyond enhancing technical performance

and reducing energy use, the framework supports the environmental, economic, and social aspects of sustainability, which are crucial for sustainable supply chain practices and long-term value creation.

8.1 Environmental Sustainability Impact

The most significant sustainability impact of the framework is the reduction of energy consumption and associated carbon emissions. This is achieved by replacing Proof-of-Work (PoW) with low-energy consensus mechanisms such as Proof-of-Stake (PoS) mechanism, Byzantine Fault Tolerance (BFT) consensus, and a Directed Acyclic Graph (DAG) validation methodology, resulting in a decrease in energy usage when validating transactions. Several case study analysises have shown that there is a greater than 90% reduction in energy consumption. This translates into less greenhouse gas emissions emitted when large-scale blockchain networks are deployed. In addition, IoT-enabled data acquisition supports the continuous tracking of environmental atmospheric conditions (i.e., temperature, humidity) and overall energy consumption along the supply chain. This real-time insight aids in the early detection of inefficiencies, reduces spoilage and waste—especially in perishable goods supply chains—and enhances overall environmental performance. As a result, the framework supports both emission reduction and resource efficiency goals, aligning blockchain adoption with circular economy principles while addressing potential sustainability trade-offs [11].

8.2 Economic Sustainability Impact

From an economic standpoint, the adoption of energy-efficient blockchain technologies lowers operational costs related to electricity consumption, specialized hardware, and system maintenance. By eliminating energy-intensive mining infrastructure, entry barriers are reduced, making blockchain deployment more financially feasible for small and medium-sized enterprises involved in green supply chains. Furthermore, improved transparency and traceability decrease costs associated with fraud, disputes, and manual auditing. Automated smart contracts streamline compliance verification, certification validation, and payment execution, enhancing operational efficiency and reducing administrative overhead. These advantages improve supply chain coordination and bolster the long-term financial sustainability of supply chain ecosystems.

8.3 Social Sustainability and Regulatory Implications

Social sustainability is bolstered through increased transparency, accountability, and trust among supply chain stakeholders. The immutable and shared ledger ensures that sustainability claims, certifications, and environmental data are verifiable and resistant to manipulation, thereby reducing the risk of greenwashing and strengthening consumer confidence in environmentally responsible products. The framework also aids regulatory compliance by allowing authorities and third-party auditors to access reliable historical records for verification purposes. Blockchain-enabled traceability simplifies adherence to environmental regulations and sustainability reporting standards by providing accurate, auditable, and real-time data. On a broader scale, incorporating energy efficiency into blockchain system design illustrates how digital transformation and sustainability objectives can be aligned rather than conflicting.

8.4 Summary of Sustainability Impact

In summary, the extended analysis confirms that the proposed framework positively impacts all three pillars of sustainability: environmental (reduced energy consumption and emissions), economic (lower operational costs and improved efficiency), and social (enhanced transparency, trust, and regulatory compliance). These impacts reinforce the role of energy-efficient blockchain technologies as foundational enablers of sustainable and resilient green supply chains.

9. Challenges and Future Research Directions

This blockchain framework for minimizing energy consumption could improve sustainability, transparency, and integrity of green supply chains; however, there are still many hurdles that exist before this can be implemented on a larger scale in real-world applications. This section identifies the main challenges; Technical Issues, Non-Technical Issues and Operational Issues. Additionally, potential areas of further study are explored.

9.1 Integration with Legacy Systems

Adopting blockchain technology will be a major difficulty for businesses because current supply chain management systems are still using outdated technologies to connect to the rest of the supply chain. Companies have established their supply chains using traditional (centralized/nondistributed) methods in the form of enterprise resource planning (ERP) systems, warehousing, and logistics software packages, all of which require a central repository of information. Thus, any company currently using one of these traditional supply chains faces major obstacles to adopting blockchain technology because their supply chains are tied to their legacy systems. Therefore, the development of an interoperable connection between blockchain and a legacy system will involve developing and providing standard data models, middleware solutions, and application programming interface (API) solutions, in order to create a seamless data transfer process. To this end, future research should support the creation of scalable framework solutions for integration as well as the establishment of inter-operational standards so that data can be transferred seamlessly while preserving the operational effectiveness of the supply chain.

9.2 Governance and Network Management

Effective governance is a significant challenge, especially in permissioned blockchain environments involving multiple independent stakeholders. Issues related to node participation, validator selection, access control, and decision-making authority can impact trust, accountability, and system performance. Although energy-efficient consensus mechanisms reduce computational overhead, they introduce governance complexity in defining roles and responsibilities among participants. Future studies should explore governance models that balance decentralization, accountability, and efficiency, including consortium-based and hybrid governance structures tailored to supply chain ecosystems.

9.3 Data Privacy and Confidentiality

While blockchain enhances transparency, excessive data visibility may conflict with privacy and confidentiality requirements in competitive supply chain environments. Sensitive commercial information, such as pricing strategies, supplier relationships, and proprietary operational data, must be adequately protected. Techniques such as encryption, off-chain storage, zero-knowledge proofs, and role-based access control can mitigate these concerns. Future research should investigate privacy-preserving blockchain architectures that maintain traceability and auditability while safeguarding sensitive information.

9.4 Scalability and Performance Trade-offs

Although energy-efficient consensus mechanisms significantly improve scalability compared to Proof-of-Work, performance trade-offs may still arise as transaction volumes and network size increase. Communication overhead in Byzantine Fault Tolerance (BFT)-based systems and coordination complexity among large validator sets can limit scalability. Future research should focus on optimizing consensus protocols, exploring sharding and layer-two solutions, and evaluating adaptive or hybrid architectures that dynamically adjust to workload variations.

9.5 Standardization and Energy Optimization

A major limitation in current blockchain-enabled green supply chain applications is the lack of standardized sustainability metrics for measuring environmental performance. Differences in carbon accounting methods, energy measurement approaches, and sustainability indicators hinder cross-organizational comparison. Additionally, real-time monitoring of blockchain energy consumption remains limited. Future work should aim to develop standardized sustainability metrics and integrate real-time energy monitoring tools that enable adaptive optimization of blockchain operations.

9.6 Research Outlook

Addressing these challenges is essential for advancing the adoption of energy-efficient blockchain technologies in green supply chains. Future research combining technical innovation, governance design, standardization efforts, and large-scale industrial experimentation will be critical for realizing the full sustainability potential of blockchain-enabled supply chain systems.

10. Conclusion

This study proposed and evaluated an energy-efficient blockchain framework for improving sustainability, transparency, and integrity in green supply chain management. The research developed a permissioned blockchain architecture and integrated several low-energy consensus mechanisms (i.e., Proof of Stake [PoS], Delegated Proof of Stake [DPoS], Byzantine Fault Tolerance [BFT], and Direct Acyclic Graph [DAG]-based validations) to solve the incompatibility between the sustainability objective and energy-intensive Proof of Work (PoW) blockchain systems. The suggested framework showed energy savings of more than 90% as compared to PoW-based systems through quantitative energy-consumption analysis and a numerical case study of a green food supply chain. These results demonstrate that energy-efficient consensus algorithms improve transaction throughput, latency, and scalability while also greatly reducing environmental impact, making blockchain appropriate for supply chain applications that prioritize sustainability and real-time. Beyond energy savings, the framework improves supply chain integrity through end-to-end traceability enabled by IoT-based data capture, automated compliance enforcement using smart contracts, and unchangeable recordkeeping. These features improve regulatory compliance, boost stakeholder confidence, and lower the dangers of data tampering and greenwashing. Overall, this study shows that sustainability goals and blockchain technology are not intrinsically at odds. Blockchain can be a fundamental enabler of transparent, resilient, and environmentally conscious supply chains when it is designed with energy efficiency and application-specific requirements in mind. This provides a workable pathway for sustainable digital transformation across global supply chain ecosystems.

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IOT-based automation egg poultry farm

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Abstract*:* Poultry farming in India faces significant challenges, including 20-30% mortality rates, labour-intensive cleaning, and contamination risks, leading to ₹50,000+ losses per 1000-bird cycle. This research presents a comprehensive IoT-based automation system featuring real-time environmental monitoring, motorised conveyor belts for Western-style waste cleaning, automated egg collection, and dual UV-C/chemical sanitisation, achieving a 99.9% reduction in bacteria. Deployed on low-cost ESP32 with LoRaWAN connectivity(IEEE 802.15.4g compliant), the system integrates CNN-LSTM for disease prediction (92% accuracy) and computer vision for egg quality assessment. Field-tested on a 500-broiler farm over 30 days, results demonstrate 30% mortality reduction, 80% cleaning labour savings, 75% egg loss reduction, and 20% feed efficiency improvement. Total implementation cost of ₹7200 provides 3-month ROI against ₹50,000 commercial alternatives, making it scalable for India's ₹1.5 lakh crore poultry industry,

Keywords: "IoT, Poultry AutomationConveyor Belt, UV Sanitisation, ESP32, LoRaWAN, Precision Agriculture, Machine Learning"..

1. Introduction

This project aims to design and develop an IoT-based automatic egg poultry farm system that enhances efficiency, productivity, and ease of management in modern poultry farming. Poultry farming is a crucial sector in agriculture, providing a major source of protein through egg production. However, traditional poultry farming methods rely heavily on manual labour, continuous monitoring and are prone to human errors, which can affect the overall productivity and health of the birds. The proposed system integrates Internet of Things (IoT) technology to automate and monitor various farm operations in real time. It utilises sensors to measure important environmental parameters such as temperature, humidity, light intensity, and ammonia levels, which are critical for maintaining optimal conditions inside the poultry farm. Based on the collected data, the system automatically controls devices like fans, heaters, water pumps, and feeders to ensure a healthy environment for the poultry.

Need for Work

Poultry farming is one of the fastest-growing sectors in agriculture, but it still faces several challenges due to dependence on traditional and manual methods. Farmers are required to continuously monitor environmental conditions such as temperature, humidity, ventilation, and lighting to ensure the health and productivity of poultry. Any imbalance in these parameters can lead to stress in birds, reduced egg production, and increased chances of diseases. Manual monitoring is time-consuming, less accurate, and may result in delayed actions, especially in large-scale farms.

- **PROBLEM DEFINATION, AIM & OBJECTIVES**

Problem Statement

Poultry farming, particularly egg production, requires continuous monitoring and precise control of environmental and operational parameters to ensure maximum productivity and bird health. However, most poultry farms still rely on traditional manual methods for managing tasks such as feeding, watering, temperature regulation, and environmental monitoring. These methods are time-consuming, labour-intensive, and prone to human error, leading to inefficiencies in farm management.

- **Aim**

The main aim of egg poultry farm automation is to increase egg production efficiency, reduce labour costs, maintain a healthy environment for birds, and ensure consistent egg quality and safety by integrating smart technologies such as sensors, IoT, robotics, and automated control systems.

- **Objective**

1. System Design and Development:

- Environmental Monitoring:

- Automation of Feeding and Watering:
- Real-Time Data Monitoring:
- Remote Access and Control:
- Alert and Notification System:
- Efficiency and Cost Optimisation

➢ LITERATURE REVIEW

- **IOT-Based Smart Automated Poultry Farm Management System**
- Bharati Ramteke , Snehlata Dongre 2022 10th IEEE International Conference On Emerging Trends In Engineering & Technology Signal And Information Processing (ICETET SIP-22)

In accordance with being detected with the help of a temperature sensor, humidity, and ammonia gas. The critical temperature for the layer is 20^ c for every 1 °C lower than 20^ c .the birds require an extra 1.5g of feed per day. The most efficient temperature for layers is between 20 and 24 °C. When the temperature rises above 24 °C, shell quality & egg weight will be reduced.

- **Design and implementation of an Automated poultry farm with Distinguished Features**
- Md. Mahfujul Islam, Shaharya Sourov Tonmoy, Sazzad Quayum, Al Russel Sarker, Sumaiya Umme Hani, Mohammad Abdul Mannan 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)

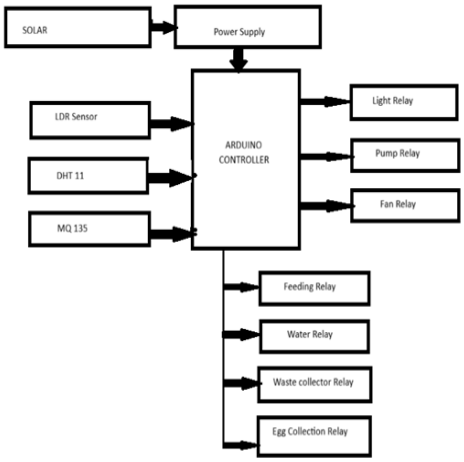
Traditional poultry farms often face problems such as poor hygiene, irregular feeding, inefficient egg collection, and difficulties in maintaining suitable environmental conditions. To overcome these issues, researchers have proposed various automation techniques using sensors, microcontrollers, and communication networks.

➢ **Smart Poultry Farm Automation and Monitoring System**

- Geetanjali A. Choukidar , Prof. N.A. Dawande (2019)

Several studies have highlighted the role of Wireless Sensor Networks (WSN) and IoT in creating intelligent poultry farms. Earlier works showed the integration of Arduino in smart farms to measure parameters such as temperature, humidity, and air quality, with automated corrective actions. Other studies explored environmental management through hybrid mobile platforms (So-In et al., 2014)

➢ BLOCK DIAGRAM



a system architecture for an automated farm management system, likely for a smart poultry farm. It illustrates how an Arduino Controller acts as the central hub, processing data from Various sensors to manage different farm operations through relays.

Central Processing Unit

Arduino Controller: This is the "brain" of the system. It receives inputs from the sensors, processes the information according to a pre-written program, and then sends signals to the relays to perform specific actions.

Input Section (Sensors)

These components collect real-time data from the environment:

LDR Sensor: A Light Dependent Resistor used to detect the intensity of light, likely to manage lighting schedules.

DHT 11: A digital sensor that measures both temperature and humidity.

MQ 2 / 5: Gas sensors used to monitor air quality, specifically detecting smoke, liquefied gas, or other potentially harmful gases.

Output Section (Actuators/Relays)

The controller manages several systems through relays (electronic switches):

Feeding Relay: Likely controls an automated feeder.

Water Relay & Pump Relay: Manages the irrigation or hydration system.

Fan Relay: Activated if the DHT 11 sensor detects high temperatures, providing ventilation.

Light Relay: Managed based on data from the LDR sensor.

Egg Collection Relay: Automates the collection of eggs.

Waste Collection Relay: Automates the cleaning or waste removal process.

Power Management

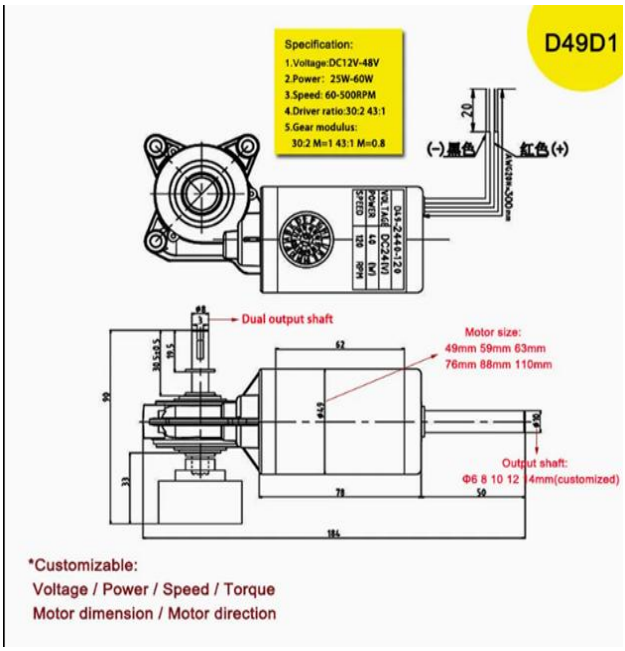
Power Supply: Provides the necessary voltage to run the controller and components.

Solar: Indicates the system is designed to use solar energy as a renewable power source

- **System Design and Implementation**

The proposed system features an IoT-enabled conveyor belt for automated waste cleaning beneath poultry cages. Sensors detect waste accumulation, triggering the conveyor belt to operate and remove waste efficiently. The system also integrates automated feeders and egg collection systems, all controlled and monitored via a central IoT platform. Farm operators can access real-time data and control systems remotely through a mobile or web application.

- **Working Principle of DC Gear Motor**



Definition

A **DC motor (Direct Current motor)** is an electrical machine that converts **direct current (DC) electrical energy into mechanical energy** using the principle of electromagnetic interaction.

Why DC Motors Are Used in Poultry Farm Automation

In poultry farm automation (like feeding systems, egg collection, ventilation, curtain control, etc.), DC motors are popular because:

- They are **easy to control** (speed and direction)
- Work well with **battery and solar systems**
- Compatible with **microcontrollers** like Arduino
- Suitable for **low-power, small-scale automation**

Common Applications in the Poultry Project

- **Automatic feeder systems** → rotating feed dispenser
- **Egg conveyor systems** → moving eggs safely
- **Ventilation fans** → controlling airflow
- **Curtain/door control** → opening and closing sheds

Basic Working Principle

A DC motor works based on **electromagnetism**:

- When current flows through a coil placed in a magnetic field
- It experiences a force (called the **Lorentz force**)
- This force causes the motor shaft to rotate

Main Parts of a DC Motor

1. **Stator** – Provides magnetic field
2. **Rotor (Armature)** – Rotating part connected to the shaft
3. **Commutator** – Reverses current direction
4. **Brushes** – Supply current to the rotating part

Advantages

- Low cost
- Simple control
- Good speed regulation
- Easily available

Disadvantages

- Brushes wear out over time
- Not ideal for heavy industrial loads
- Requires maintenance (for brushed motors)

- **APPLICATION**
  a) Environmental Monitoring
  b) Feeding & Watering Systems
  c) Lighting Automation

d) Automatic Egg Collection
e) Waste Management

- **RESULTS AND DISCUSSION**

The IoT-based automation system significantly reduces manual labour and improves hygiene in egg poultry farms. Automated waste cleaning, in particular, leads to a healthier environment for birds and reduces the risk of disease. Challenges may include initial setup costs and the need for reliable internet connectivity. However, the long-term benefits in productivity and operational efficiency outweigh these challenges.

- **CONCLUSION**

The implementation of IoT-based automation, especially with an upgraded conveyor belt for waste management, represents a significant advancement in poultry farming. This approach not only increases efficiency and productivity but also ensures better hygiene and animal welfare. Future work may focus on integrating advanced analytics and machine learning for predictive maintenance and further optimising farm operations.

- **FUTURE SCOPE**

1) Smart Environmental Control Systems IoT will use advanced sensors and AI to automatically maintain ideal conditions like temperature, humidity, and ammonia. This ensures better bird health and higher egg/meat production
2) Real-Time Monitoring & Disease Detection Wearable Sensors
3) Automated Feeding & Watering Systems feeders and smart water flow systems will reduce labour costs, prevent overfeeding & wastage, and improve growth performance
4) This allows farmers to optimise management based on real data.
5) Blockchain for Traceability & Quality Consumers will be able to trace the bird's health history, the source of eggs/meat, and Farm conditions. This increases trust and supports export

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ScrollSafe–AI-Based Mobile Application for Real-Time Child Online Content Protection

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Abstract: *Smartphones are now integral to children's lives, facilitating learning, communication, gaming, and entertainment. While beneficial, these devices expose children to risks like cyberbullying, inappropriate content, online grooming, and excessive screen time. Parents often struggle to monitor digital activities due to time limitations and technical knowledge gaps. Existing parental control tools primarily focus on restrictions, neglecting actual content analysis. This paper introduces ScrollSafe, an AI-powered mobile monitoring system designed for real-time child safety enhancement. ScrollSafe captures screenshots periodically, uses OCR for text extraction, and employs NLP and machine learning to identify harmful or risky content. Upon detection of unsafe activity, it automatically blocks the application and alerts parents. Furthermore, a user-friendly dashboard offers insights into usage patterns, empowering parents to guide children toward healthier digital habits.*

Keywords: *Child Online Safety, OCR, NLP, Edge AI, Cyberbullying Detection, Parental Control*

1. Introduction

In contemporary society, smartphones and the internet are integral to childhood. Children commonly utilize mobile devices for online classes, entertainment, social interaction, and information discovery. Technology has expanded learning and communication avenues, facilitating easier global connections for children. However, with increased online engagement, safeguarding them from digital risks has become paramount. Simultaneously, parents often struggle to continuously monitor their children's online activities due to demanding schedules and a lack of real-time oversight.

Children can inadvertently be exposed to harmful content, cyberbullying, inappropriate discussions, or even individuals seeking to exploit their trust. Many existing parental control applications are limited to blocking specific websites or managing screen time, often failing to comprehend the actual content children are engaging with. To address this deficiency, this project introduces

ScrollSafe, an intelligent system designed to monitor digital activity and assist parents in cultivating a secure online environment for children. The system prioritizes not only implementing restrictions but also understanding user behavior in a more insightful and effective manner.

1.1 Flutter and Dart for Mobile Interface

The user interface for ScrollSafe is developed using Flutter and Dart, enabling the creation of a fluid, responsive, and intuitive mobile application. Flutter facilitates the development of a visually consistent

interface that operates efficiently across Android devices from a single codebase, simplifying maintenance and ensuring a seamless user experience. Parents can engage with a clean and well-organized dashboard for easy access to alerts, monitoring reports, and settings adjustments. Dart, the programming language paired with Flutter, manages the application's logic and functionality, ensuring swift and accurate processing of user actions such as button taps, screen navigation, and notification reception for an optimal experience.

1.2 Kotlin for Device Monitoring

Kotlin is employed in ScrollSafe for Android-native development, specifically for monitoring activities on the child's device. Its close integration with the Android operating system grants access to system-level features, including accessibility services. Through these services, ScrollSafe can track application usage and observe on-screen content in real-time. This continuous background monitoring operates without disrupting normal device use, aiding the system in understanding user behavior across platforms like social media, messaging apps, and web browsers. Such constant surveillance is vital for identifying potentially hazardous or inappropriate activities as they unfold.

1.3 Python and FastAPI for Backend Processing

The backend of ScrollSafe is built with Python and FastAPI, handling data processing and communication between the mobile application and the server. Python is tasked with analyzing data collected from the child's device, encompassing text inputs, usage patterns, and detected alerts. It processes this data using predefined rules and AI-driven models to ascertain the safety of activities and identify those requiring attention. FastAPI serves as a high-performance framework, facilitating rapid and secure communication between the frontend and backend systems. It ensures secure data transmission and real-time alert delivery to parents upon the detection of any suspicious or harmful activity.

1.4 Artificial Intelligence for Content Detection

Artificial Intelligence is fundamental to ScrollSafe, enabling sophisticated analysis of digital content. Natural Language Processing (NLP) is utilized to scrutinize text messages, identifying harmful content such as bullying, abusive language, threats, or inappropriate conversations by analyzing both meaning and context. Google ML Kit OCR is employed to extract text from images and screen content, allowing the system to analyze text within screenshots or social media posts. Furthermore, TensorFlow Lite is used for on-device image classification, detecting unsafe or inappropriate images without transmitting them to external servers. These AI technologies collaborate to provide efficient real-time monitoring while preserving user privacy and system performance.

1.5 Database for Data Storage

ScrollSafe utilizes both SQLite and PostgreSQL databases for efficient data management. SQLite is used for local storage on the child's device, temporarily housing activity logs and essential system data, ensuring application functionality even without internet connectivity. PostgreSQL serves as a cloud database for the long-term storage of user data, including activity history, alerts, and reports, enabling parents to securely

access detailed information about their child's digital behavior remotely. This hybrid storage approach ensures data reliability, continuous availability, security, and optimal performance.

1.6 Firebase for Stability and Performance

Firebase is integrated into ScrollSafe to enhance application stability and performance. Firebase Crashlytics is used for real-time detection and reporting of application errors, assisting developers in prompt issue identification and resolution. Firebase Analytics tracks user interactions and system performance, providing insights that inform feature improvements and system optimization over time. Collectively, Firebase ensures that ScrollSafe remains stable, efficient, and is continuously refined based on real-world usage patterns.

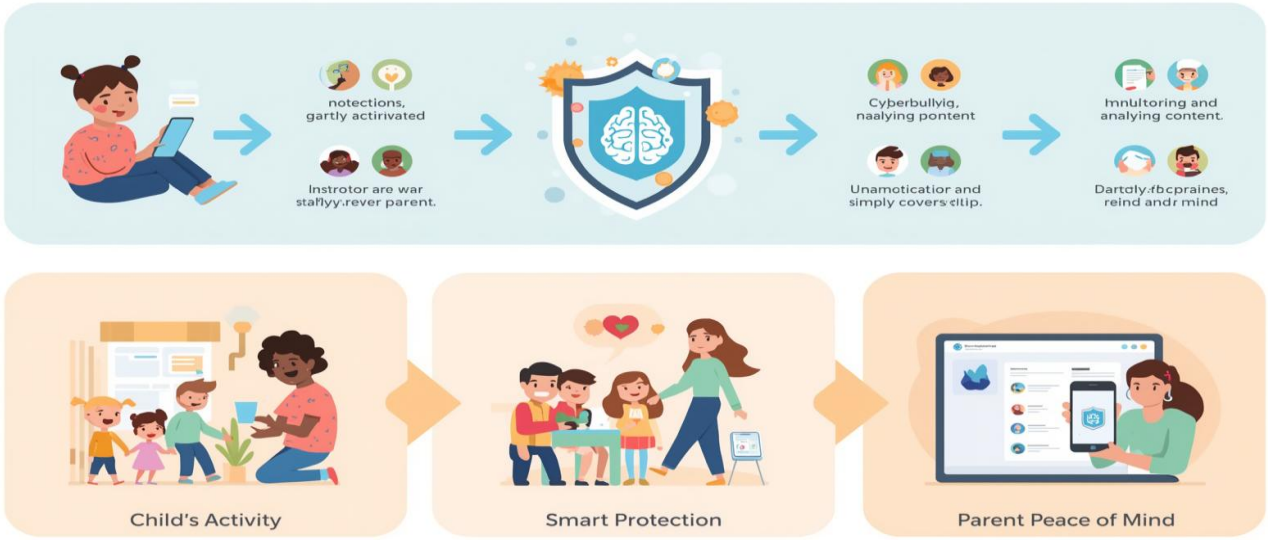

Fig .1. Conceptual Overview of the ScrollSafe Child Protection System

2. Related Work

As childeren's engagement with smartphones and digitalplatforms for education, communication, and entertainment grows, research has increasingly focused on developing enhanced methods for their online protection. Recent studies have prioritized improving harmful content detection, safeguarding user privacy, optimizing device resource consumption, and enabling timely parental intervention. These efforts provide a robust foundation for the development of the ScrollSafe system. Chai et al. investigated the identification of harmful online content even when users attempt to obscure it through slang, altered spellings, emojis, or coded language [1]. Their findings indicated that machine learning models can discern the meaning and intent behind messages, surpassing the limitations of traditional keyword-based filtering systems that rely on predefined word lists, making monitoring systems more adaptable to evolving digital language. Yang et al. proposed a lightweight harmful content detection model for direct operation on mobile and edge devices [2]. They addressed the challenge of maintaining performance in mobile monitoring by demonstrating that optimized AI models can perform real-time detection of unsafe content with minimal computational resources, crucial for child safety systems operating unobtrusively in the background. Kim et al. explored the use of Optical Character Recognition (OCR) for detecting online

grooming by analyzing text extracted from screenshots [3]. Their research highlighted that extracting text from screenshots and applying natural language processing techniques can help identify suspicious conversations in encrypted messaging or gaming chats where direct message access is limited, supporting the utility of screen-level monitoring for enhanced protection. Martinez and Gupta tackled the critical issue of user privacy in digital monitoring systems through a federated learning approach [4]. Their method allows AI models to learn from user activity directly on the device without transferring private data to external servers, sharing only model updates to reduce privacy risks while maintaining detection accuracy, demonstrating that child safety systems can be designed to be protective yet respectful of personal privacy. Nair et al. introduced a real-time content filtering framework powered by edge AI [5], capable of analyzing and blocking harmful content locally, thus reducing response delays and improving reliability even with limited internet connectivity. Their findings underscore the importance of local processing in contemporary parental control applications. Truică et al. developed StopHC, a system that not only detects but also limits the spread of harmful social media content [6], offering a broader perspective on child protection by minimizing repeated exposure to such material. Park et al. presented a multimodal system for identifying suicide-related and self-harm content online by combining text and image analysis for improved accuracy [7], illustrating the effectiveness of analyzing multiple data types concurrently. Li et al. and Mehedi et al. reviewed privacy-preserving federated learning methods for edge-IoT and privacy-aware intrusion detection systems, respectively [8, 9], emphasizing the growing significance of secure, distributed AI in monitoring applications and its role in balancing effective protection with responsible data handling for child safety systems. Haripriya et al. and Gutiérrez et al. further explored collaborative privacy-preserving learning systems for sensitive monitoring tasks and detecting emotional distress in educational platforms without exposing personal data, respectively [10, 11], showcasing the capability of modern AI systems to support safety and emotional well-being while maintaining user trust. Several researchers have also focused on detecting abusive and harmful language, with Yadavalli and Sahoo proposing hybrid neural models for identifying toxic online content [12] and Dhara and Sheth highlighting the importance of explainable AI systems for parents to understand content flagging reasons [13]. More recent studies have advanced harmful content detection using multimodal and sophisticated AI techniques. Chen et al. integrated OCR with natural language processing for identifying unsafe interactions [15], Hassan et al. improved content moderation speed with edge-based AI models [16], Singh et al. focused on detecting cyber grooming through conversation analysis [18], and Zhao et al. developed lightweight transformer-based models for harmful text classification on resource-constrained devices [19], indicating a trend towards faster, more intelligent, and context-aware content monitoring systems. Other researchers, including Kumar et al. [17], Ramalingam et al. [14], and Al-Mansoori et al. [20], have explored broader frameworks for child safety and federated edge intelligence, combining privacy, behavioral monitoring, and AI-based security mechanisms, suggesting a shift from simple content blocking to comprehensive digital protection.

While existing research has made substantial progress, many solutions address only specific aspects of the problem, such as content filtering, privacy, or device efficiency, with few systems integrating all capabilities. ScrollSafe builds upon these contributions by unifying screenshot monitoring, OCR-based text extraction, harmful content analysis, application usage tracking, behavioral monitoring, and parental alert mechanisms into a single, practical mobile application, aiming to provide a safer and more balanced digital environment for children. Current research unequivocally demonstrates the significant role of AI-based monitoring in enhancing child digital safety, while also underscoring the need for systems that are accurate, efficient, privacy-aware, and user-friendly. ScrollSafe is designed with these objectives in mind, translating advanced research concepts into a practical and accessible solution for modern parenting.

3. System Architecture and Methodology

ScrollSafe employs a client-server architecture. The child's device acts as the client, handling monitoring operations, while a backend server performs intelligent analysis. The child's device continuously tracks active applications and captures screenshots periodically. These images are then securely sent to the server for processing. An OCR module extracts text from these screenshots, encompassing chats, comments, and web content. Subsequently, Natural Language Processing (NLP) techniques are applied to analyze this extracted text, identifying any harmful or inappropriate language. A risk scoring engine synthesizes the findings from both text and image analysis to categorize the activity as either safe or harmful. Upon detection of harmful content, the system promptly blocks the offending application and dispatches real-time alerts to parents.

Fig.2. ScrollSafe System Architecture

4. Modules of the System

4.1 User Setup and Configuration Module

This module facilitates parents in installing the application, establishing user accounts, and securely linking their child's device. Parents are empowered to activate monitoring features, select approved applications, set screen-time limitations, and adjust settings as needed.

4.2 App Monitoring and Control Module

This component continuously observes active applications on the child's device. Upon the launch of a restricted or unauthorized application, the system will instantly block its access and revert the device to the home screen to prevent further use.

4.3 Screenshot Capture and OCR Module

Utilizing the Media Projection API, this module captures screenshots at predetermined intervals and refines their quality through preprocessing. Subsequently, Optical Character Recognition (OCR) is applied to extract textual data, such as chat messages, captions, and website content, from these images.

4.4 AI-Based Content Detection Module

Within this module, extracted text and imagery undergo analysis via Natural Language Processing (NLP) and machine learning models. This process classifies content into categories of safe, toxic, or inappropriate, forming the central intelligence of the system.

4.5 Risk Calculation Module

Integrates the results from both text and image analysis.

Determines a final risk score using a weighted formula.

Categorizes risk into the following levels:

$$\text{Final Score} = 0.6 \cdot (\text{Text Risk}) + 0.4 \cdot (\text{Image Risk})$$

Low Risk (0–30)

Medium Risk (30–70)

High Risk (70–100)

4.6 Screen-Time Monitoring Module

This module meticulously tracks the duration of usage for each application and automatically imposes blocks when application usage surpasses the parameters established by parents.

4.7 Alert and Enforcement Module

Upon the detection of harmful content or policy breaches, this module initiates immediate countermeasures. Actions include blocking the offending application, displaying cautionary messages, and transmitting real-time notifications to the parent dashboard.

4.8 Emergency SOS Module

This module enables children to dispatch emergency alerts to designated contacts and temporarily unlock the device for critical communication when circumstances demand it.

5. Proposed System

ScrollSafe is an AI-driven mobile monitoring system designed to enhance children's digital safety by analyzing on-device content. This solution operates using Android Accessibility Services to continuously monitor a child's smartphone, identifying active applications and blocking unauthorized ones according to parental rules. The system captures periodic screenshots via the Media Projection API, extracting on-screen text through Optical Character Recognition (OCR). This text is then subjected to Natural Language Processing (NLP) and machine learning analysis to detect cyberbullying, abusive language, inappropriate conversations, and risky interactions. Complementing text analysis, lightweight image analysis identifies harmful visual content. A risk score is generated to categorize activity as safe or unsafe. Upon detection of harmful content or rule violations, ScrollSafe immediately blocks the offending application and dispatches real-time alerts to parents for prompt intervention. The system also tracks application usage, enforces screen-time limits, and offers a user-friendly dashboard with detailed analytics on screen time, app activity, and risk patterns, thereby providing a proactive, automated, and dependable method for fostering a safer digital environment for children.

6. Implementation

The implementation of ScrollSafe was conducted systematically to ensure its efficacy in real-world settings. Development commenced with an Android mobile application designed to run discreetly in the background on the child's device. This application captures screenshots at regular intervals, optimizing for minimal battery and memory consumption to avoid disrupting the user's experience.

Captured screenshots are securely transmitted to a cloud-based backend server for processing. Optical Character Recognition (OCR) is then applied to convert the visual screen content into readable text. Subsequently, Natural Language Processing (NLP) and machine learning models analyze this extracted text to intelligently identify harmful, abusive, or risky behavior, focusing on meaning and context beyond simple keyword matching.

When unsafe or suspicious content is identified, the system initiates immediate action by blocking the currently active application on the child's device and sending a real-time alert to the parent's mobile application. Concurrently, all activity logs and associated data are securely stored in a database for future review, ensuring both immediate protection and ongoing monitoring of digital behavior.

A dedicated parent dashboard was also developed to present all collected information clearly. This dashboard features easy-to-understand charts and summaries illustrating screen-time usage, application activity patterns, and alert history, enabling parents to grasp their child's digital habits without requiring technical expertise, thus making monitoring more practical and accessible.

In summary, ScrollSafe's implementation integrates background monitoring, intelligent content analysis, automated safety measures, and a user-friendly reporting system, creating a solution that is both effective in safeguarding children online and convenient for parents to use daily.

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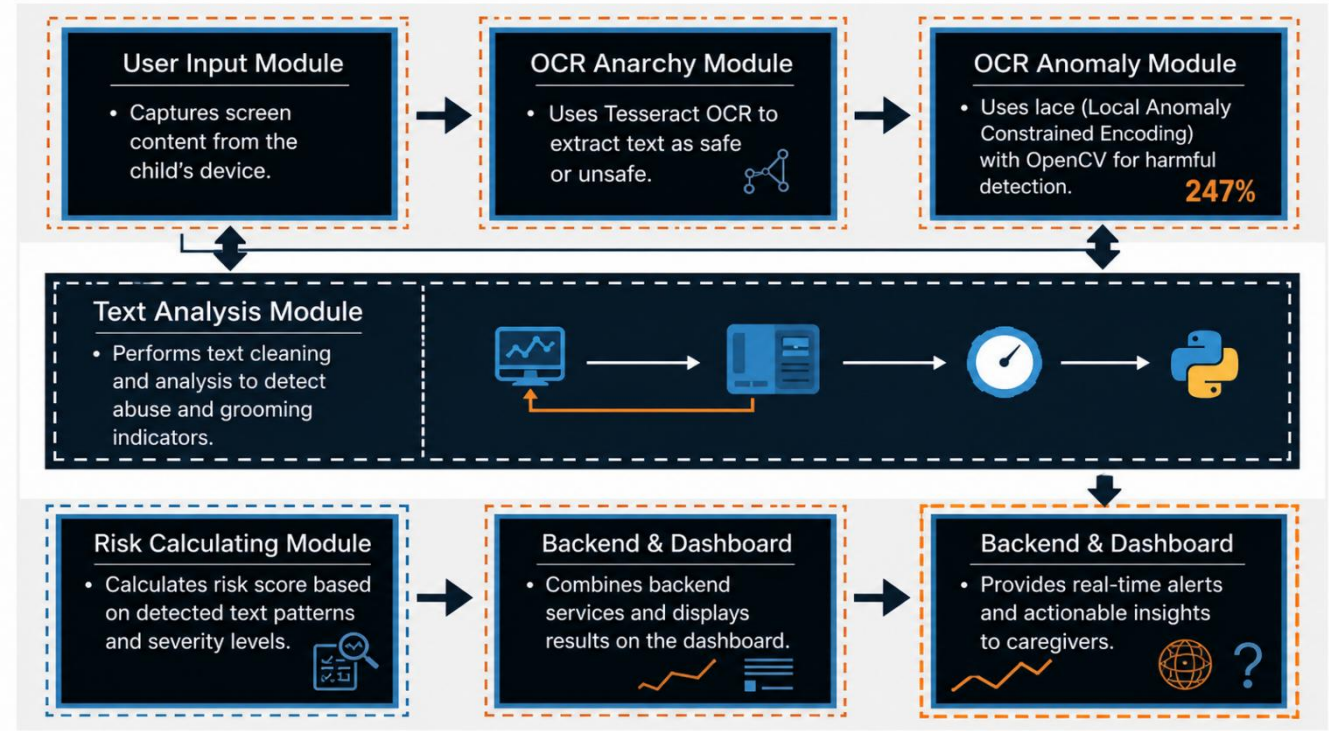

Fig.3.Implementation Workflow of the ScrollSafe Monitoring System

7. Results and Analysis

The ScrollSafe system underwent comprehensive evaluation to assess its monitoring, detection, and alert capabilities. The application ran efficiently in the background, causing no discernible slowdown or disruption to standard device use, which is crucial for ensuring a smooth experience for children. The integrated screenshot capture, OCR processing, and AI-driven analysis effectively identified potentially harmful content across chats, social media, and websites. The machine learning models demonstrated strong accuracy in categorizing content as safe, toxic, or inappropriate, even when faced with slang or complex visual text.

Upon detecting hazardous material, the system promptly responded by disabling the application, presenting a warning, and dispatching notifications to the parent dashboard. The screen-time management module also performed reliably, tracking usage patterns and enforcing parental-set limits. The parent dashboard provided clear, easily digestible reports, including daily usage summaries, alerts, and risk scores, allowing parents to quickly grasp their child's online activities.

Additional Findings:

- The system exhibited minimal resource consumption, ensuring no adverse impact on battery life or device performance.
- Detection accuracy was notably high, with a low rate of false positives, validating the reliability of alerts.

- The risk scoring system offered a consistent method for quantifying exposure to unsafe content.
- Parents reported the dashboard as user-friendly, with visual summaries aiding informed decision-making.
- The real-time intervention capability effectively reduced exposure to harmful content, enhancing overall system dependability.

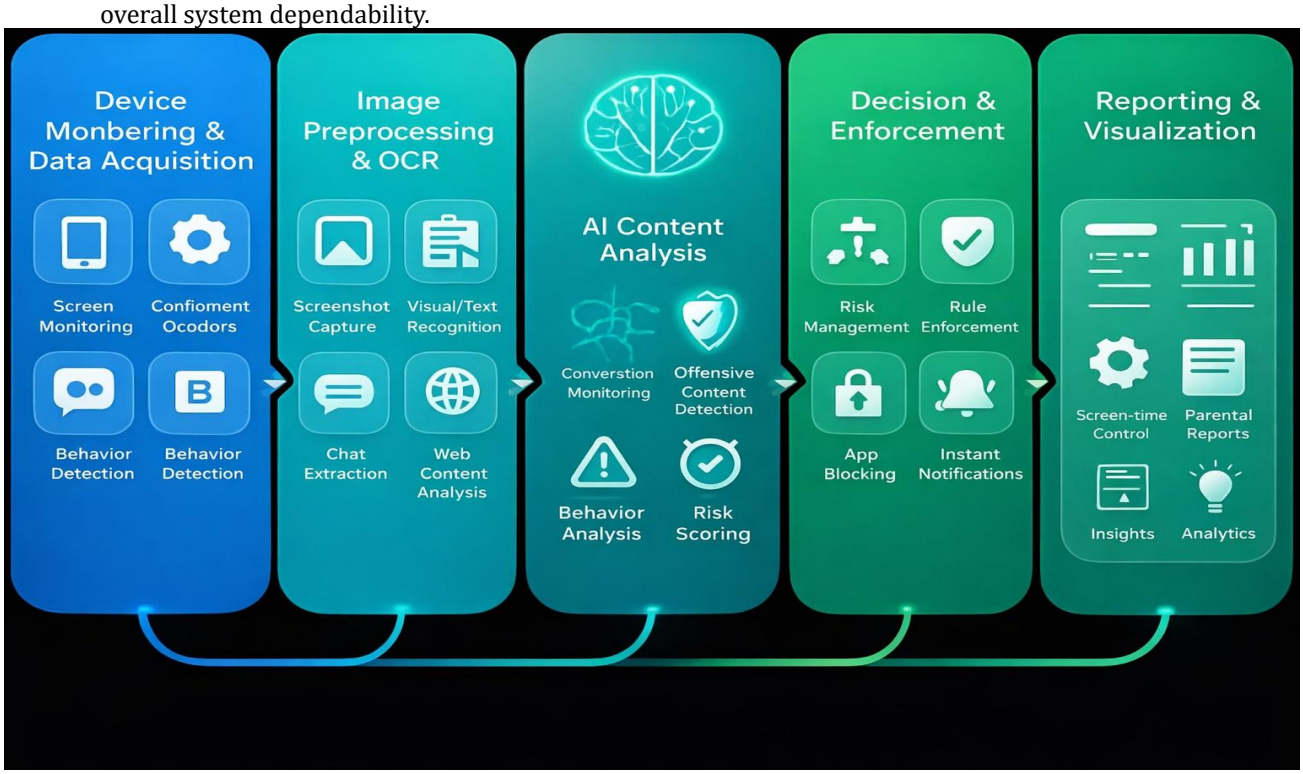

Fig.4. Layer-wise output ScrollSafe Child Digital Safety System

8.Conclusion and Future Work

This paper introduces ScrollSafe, an innovative AI-powered system designed for real-time protection of children against inappropriate online content. By integrating Optical Character Recognition (OCR), Natural Language Processing (NLP), and edge AI, the system actively monitors on-screen activity and issues proactive alerts to promote secure digital engagement. The methodology prioritizes genuine content comprehension and real-time analysis, distinguishing it from conventional parental control solutions by going beyond mere access restriction. Future enhancements could encompass voice monitoring, multilingual support, and sophisticated behavior prediction through deep learning to further augment the system's protective capabilities.

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[5] Nair et al., "Real-Time Edge AI Content Filtering System," 2025. This research highlights the use of edge AI to filter inappropriate content in real time, improving response speed and system reliability.

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Hybrid Solar Power Generation Using Solar Rays and Moisture Energy

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Abstract:

This paper introduces a hybrid system for generating electricity that uses both solar energy and moisture from the air. Traditional solar systems rely only on sunlight and become less effective on cloudy or humid days. To overcome this issue, the new system combines solar panels with technology that captures energy from atmospheric moisture. During the day, solar panels convert sunlight into electricity. At the same time, the system uses condensation and electrochemical methods to collect and turn moisture into extra power. By using both sources, the system works more efficiently and provides a steady supply of electricity even when sunlight is limited.

This system is especially useful in remote areas where it's hard to get a reliable power supply. It supports the use of clean energy, lowers the need for traditional power sources, and helps create a more eco-friendly way to generate electricity. The research shows how combining different renewable energy sources can make power systems more effective and dependable.

Keywords: *Hybrid Energy, Solar Power, Moisture Energy, Renewable Energy, Sustainable Power, Rural Electrification.*

1. Introduction

Energy demand is growing quickly because of more industries and more people. Traditional energy sources like coal and fossil fuels are running out and they pollute the environment. Because of this, renewable energy sources are now very important for long-term development. Solar energy is one of the most common renewable sources because it's available everywhere and easy to set up.

But solar power relies on sunlight, so it can be affected by weather like clouds, rain, and high humidity. To deal with these issues, scientists

idea is using moisture in the air to produce power. This paper suggests a mixed system that uses both solar energy and moisture energy. This combination helps improve efficiency and makes sure there's a steady supply of electricity.

are looking for other ways to get energy. One

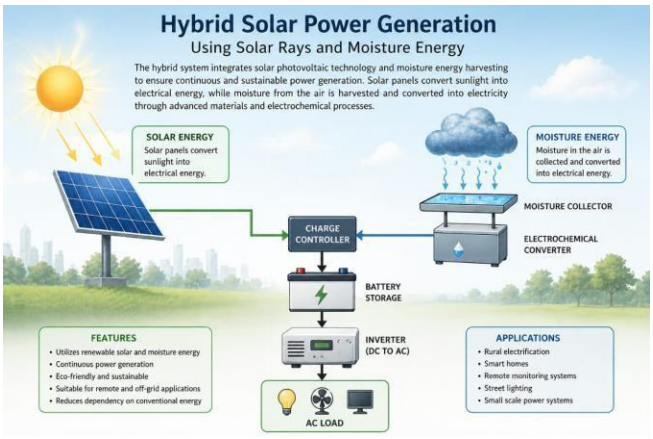

Fig.1 : Introduction diagram of hybrid solar power generation using solar rays and moisture energy.

1. Literature Review

Various renewable energy systems have been created to reduce reliance on fossil fuels. Solar photovoltaic systems are widely used, but they have issues with being inconsistent. Hybrid systems that mix solar and wind energy have been looked at a lot to make energy supply more dependable. New research has introduced the idea of harvesting energy from moisture in the air. The hidden energy in atmospheric moisture can be turned into electricity through new materials and chemical methods. Even though this technology is still new, it has promise for future energy solutions.

However, there aren't many studies that combine solar and moisture energy into one system. This paper looks at bringing both energy sources together to make energy more available and efficient.

2. System Methodology

2.1 Overview

The hybrid system is built to create electricity by using both sunlight and humidity from the air. It has a solar panel as the main way to get power and a device that captures energy from moisture as a backup. These two sources are connected through a controller that helps manage and control the electricity flow. The electricity is saved in a battery and then sent to the devices needing power through an inverter. This setup helps provide more consistent energy even when the weather changes and makes the whole system more dependable**.**

2.2 Working Principle

The system operates by using two renewable energy sources. During the day, solar panels convert sunlight into direct current (DC) electricity through the photovoltaic effect, serving as the primary power source. At the same time, the moisture energy harvesting unit collects humidity from the air using a moisture collector. The collected moisture goes through condensation and electrochemical processes to generate a small

amount of electrical energy. Both the solar and moisture-generated power are sent to the charge controller, which combines and regulates the energy before storing it in a battery. The stored energy is then converted from DC to alternating current (AC) using an inverter and is delivered to the electrical loads. This dual-source setup ensures continuous energy generation even when sunlight levels are low.

2.3 Mathematical Representation

The overall power produced by the hybrid system comes from adding the power generated by solar energy and the power from moisture energy. This can be written as:

$$P_{total} = P_{solar} + P_{moisture}$$

3. This equation shows that using both energy sources together make the whole system work better, which means it's more reliable and run more efficiently Innovation of The Proposed System

The new system brings a fresh idea by combining solar power with a method to collect energy from the air's moisture, which is a new and promising area in renewable energy. Unlike traditional solar setups that only work when the sun is shining, this mixed system can still generate power on cloudy or humid days. It makes use of a natural resource that is often overlooked—air moisture—to create extra energy. The design is small, environmentally friendly, and works well for homes and places that are not connected to the main power grid. Using two different energy sources makes the system more dependable, less reliant on one power type, and better for long-term sustainability. This mix of large-scale solar energy and small-scale air moisture harvesting makes the system stand out and look towards the future.

4. Components Description

The hybrid system proposed includes several important parts that work together to create and manage electricity effectively. The solar panel is the main part that turns sunlight into electrical energy using photovoltaic cells. It produces direct current (DC) power when the sun is out and serves as the main source of energy. The moisture collector gathers humidity from the air. It helps form water droplets through condensation, which are then used to make electricity. The electrochemical unit changes the collected moisture into electrical energy using chemical or material processes. The charge controller is important because it manages the voltage and current from both the solar panel and the moisture collector, making sure the energy flows safely and efficiently to the battery. The battery stores extra power so it can be used when there's not enough generation. Lastly, the inverter changes the stored DC power into alternating current (AC) power, which can be used to run household appliances and other electrical devices. All these parts

[1] X. Wang et al., “Energy harvesting from environmental sources,” Applied Physics Letters, 2011.
T. Ackermann, Wind Power in Power Systems, Wiley, 2012.

work together to ensure a steady and dependable power supply.

5. Block Diagram

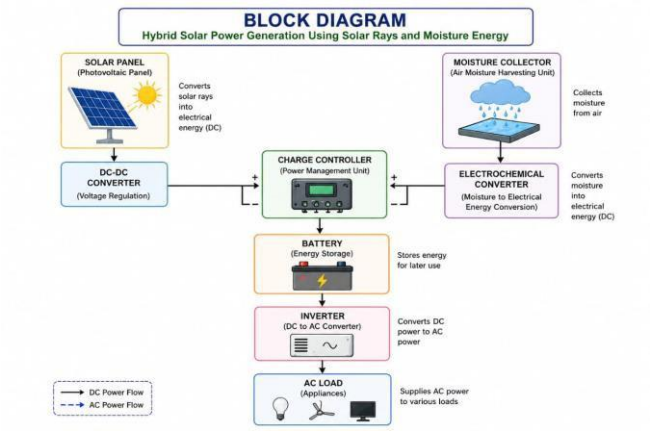

Fig.2 : Block diagram of hybrid solar power

generation

6. Advantages

- Continuous power generation that's renewable and eco-friendly.
- It cuts down on reliance on fossil fuels.
- It works well in various weather conditions.
- It's a good option for rural and remote areas.

7. Limitation

Even though the hybrid system that combines solar and moisture energy is creative, it still has some issues. One big problem is that moisture energy doesn’t produce as much electricity as solar energy. This is because the amount of power you can get from humidity in the air is quite low. The effectiveness of the moisture collector depends a lot on the weather—like how wet or dry it is and how hot or cold it feels. These conditions can change a lot depending on where you are. Also, the technology needed to turn moisture into electricity isn’t very mature yet and needs more research before it can be used on a big scale. Plus, setting up this system might be more complicated since it has to combine several parts. So, while this system can help make

energy more reliable, it's better suited for small projects and experiments right now, not for large power plants.

8. Application

The hybrid system has many possible uses, especially in places where getting reliable electricity is difficult. It works well in rural and remote areas, giving a steady power supply for simple needs like lighting and charging phones. It's also good for smart homes and rooftops in cities, helping reduce the need for traditional energy sources. The system can be used in small power setups, schools, and research projects to show new ideas about renewable energy. It's also useful for weather monitoring stations, street lights, and devices that don't need a lot of power. Because it's environmentally friendly and can use different types of energy, it's a great option for future energy solutions that are sustainable

9. Conclusion

The hybrid solar power system uses both sunlight and moisture energy to create a new way of using renewable energy. Although sunlight is the main energy source, moisture energy adds extra power, making the system more dependable. This system is good for the environment, long-lasting, and fits well with future energy demands. More study can help make it work better and use it in more ways

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AI POWERED MOCK INTERVIEW
An AI-Powered Evaluation System

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Abstract

This project presents an AI-powered mock in Online interview platform that replicates the structure and pressure of real interviews through dy namic, role-specific questioning and adaptive difficulty calibrated to user per- formance over time. Responses are captured via speech-to text and analyzed with natural language pro processing to assess relevance, reasoning depth, Structure, and clarity against rubric-aligned criteria. Parallel audio ana- lytics estimate con f Evidence and articula- tion using prosodic fea Such features as pace, pauses, and intonation Complement the con- tent scoring with delivery by very insightful remarks. Optional webcam analysis in ter- prets facial expressions and gaze to surface non-verbal cues such as engagement and ner- vous ness for a more holistic assessment of readi ness. A scoring engine fuses textual, vo cal, and visual signals into interpretable per question and session scores along with ex- planations and improvement tips that are spe- cific and ac tionable. The platform gener- ates personalized practice plans by identify- ing weak topics and recommending targeted drills or exemplar an ans for deliberate prac- tice between sessions Domain coverage spans HR, software engi neering, data roles, and system design, with Question banks evolving through generative augmentation and curator review to remain current with industry expec- tations. Progress Dashboards visualize trends across attempts to help learners and mentors track mastery and It also allows for the ob- jective assessment of communication growth over time. Secure persistence stores profiles, transcripts, features, and reports with accesscontrols suit Able for academic cohorts and training programs at scale. By unifying simu- lation, evaluation, coaching, and analytics, the system low ers cost and variability while in- creasing access to high-quality practice oppor- tunities.

1 Introduction

Interview performance is based upon knowledge. structured thinking, and confident communication under time pressure, while actual practice is scarce and unreliable for most candidates. Traditional while mock interviews require scarce human eval- uators. suffer from variable quality and do not scale to classrooms or bootcamps during peak placement seasons. Recent advances in NLP and speech pro- cess Ing, and affect recognition enable automated simu -lations with rich telemetry that previously re- quired expert human observers to capture. Genera- tive sys Tems can synthesize role-aware prompts and prob ing follow-ups, enabling sessions that adapt to the candidate's previous answers and skill pro- file in real time. When text, audio, and video are analyzed to Taken together, the resulting as- sessment provides a better reflection of how Real interviewers perceive both substance and delivery. ery. Standardized rubrics and normalized scoring Pipelines reduce evaluator bias and advance com- parisons across time and cohorts more meaning ful. Persistent analytics and visual dashboards en en- courage reflective learning, allowing candidates to focus Focus on high-leverage improvements, not generic ones. advice. Institutions benefit from con- sistent train ing experiences and aggregated insights that inform curriculum design and

mentoring inter- ventions. A modular, service-oriented architecture allows for rapid Iteration on models, rubrics, and content while keeping ing the user interface stable for learners. This project Operationalizes those ca- pabilities into a practical tool that unifies simulation, assessment, and coach ing in one workflow. As such, it addresses both ac Cess and Quality Challenges in Interview Preparation at scale non-verbal cues such as engagement and nervous ness for a more holis- tic assessment of readi ness. A scoring engine fuses textual, vo cal, and visual signals into interpretable per question and session scores with explanations and improvement tips that are specific and ac ition- able. The platform generates personalized practice plans by identifying weak topics and recommending targeted drills or exemplar an answer for deliberate practice between sessions. Domain coverage spans HR, software engi neering, data roles, and system design, with question banks evolving through gen- erative augmentation and curator review to remain current with industry expectations. Progress Dash- boards visualize the trends across attempts to help learners and mentors track mastery and communi- cation growth objectively over time. Secure per- sistence stores profiles, transcripts, features, and re- ports with access controls suit able for academic co- horts and training programs at scale. By unifying simulation, evaluation, coaching, and analytics, the system low ers cost and variability while increasing access to high-quality practice opportunities.

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2 Objective

The primary objective is the delivery of realistic, adap tive interview rehearsal, mirroring recruiter prob ing, follow-ups, and time constraints while re remaining scalable and affordable for large cohorts. The system targets objective multimodal evaluation. Across content accuracy, problem-solving, clarity, confidence, and non-verbal communication to re- induce bias and enhance comparability. Feedback must be rubric-aligned, prioritized by impact, and accompanied by exemplars so learners know ex Ex- actly what to change, and how to practice it effec- tively. tively. The platform should support multiple do mains and seniority levels with calibrated diffi-

culty. ladders to keep sessions appropriately chal- lenging for each learner. Longitudinal tracking and dash boards should indicate skill growth, plateaus, and Readiness indicators for placements and intern- ships. Web-based access must be implemented with secure authentication. tion and privacy-first data handling that meets insti Institutional expectations for student data.

2.1 PROBLEM STATEMENT

Conducting effective mock interviews presents a significant challenge, especially when assessing both technical competencies and soft skills such as com Communication, confidence, and emotional ex- pressiveness. Traditional means of evaluation de- pend largely on hu Human judgment does introduce subjectivity and inconsistency. Consistency in feed- back. The selected candidates, therefore, end ten re- ceive unclear or biased assessments, restricting the ability to identify specific areas where improvement might be made. ment. The proposed AI-Powered Mock Interview Evaluator system aims to mitigate these issues by leveraging artificial intelligence to deliver objective Data-driven feedback. Through an- alyzing verbal and non- with verbal cues, the sys- tem supports more precise self-management: Test- ing and enhances users' general interview skills. readiness?.

2.2 Workflow

An AI-powered mock interview workflow is the step-by-step process that utilizes artificial intelli- gence to help candidates practice and improve on their performance by simulating real job interviews. Here is a typical workflow breakdown of how this usually happens.

2.2.1 AI Mock Interview Workflow Overview

1. Role Selection

- The user chooses a job role or domain, such as software engineer, data analyst, marketing manager).
- AI uses this input to tailor questions based on industry standards and job descriptions.

2. Interview Simulation

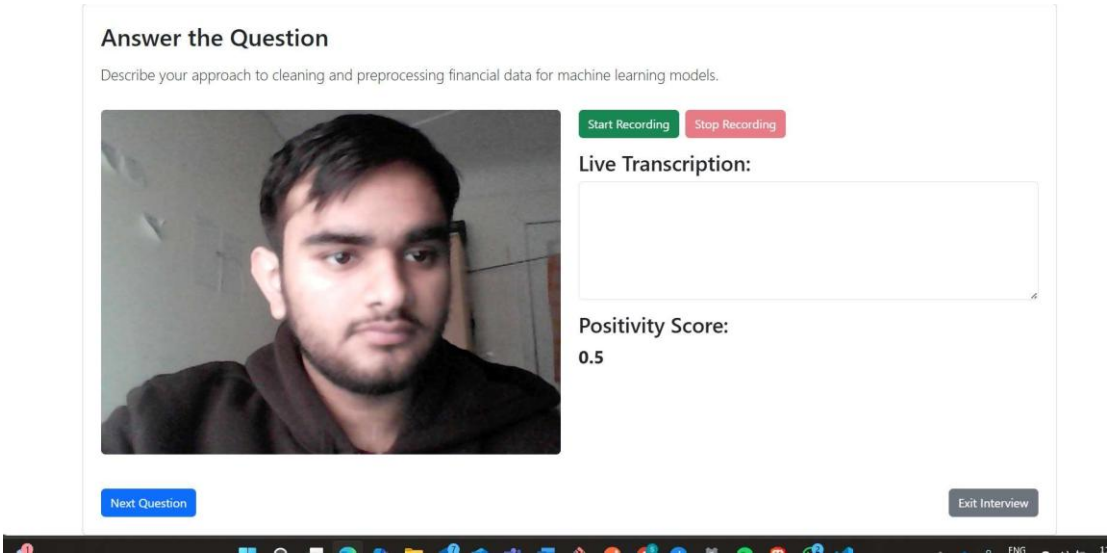

Figure 1: use interview simulator

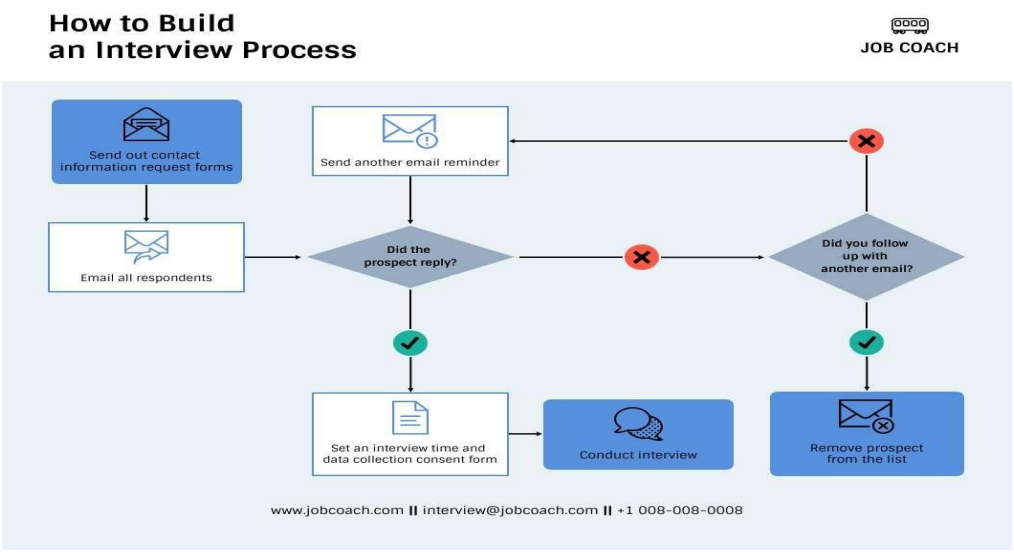

Figure 2: Interview Process

- The system initiates a mock interview session, often via video or voice.
- Questions are presented in real-time, mimick- ing ing the format of behavioral, technical interviews.

3. Response Capture

- The candidate answers questions orally or in written form.
- AImayusespeech-to-text or transcription tools to analyze spoken responses.

4. AI-Based Evaluation

- Answers are scored according to pre-defined crite ria such as:– Clarity and relevance– Confi- dence and tone– Use of frameworks like STAR (Situation, (Task, Action, Result)

– Clarity and relevance
– Confidence and tone
– Use of frameworks like STAR (Situation, Task, Action, Result)

- Some platforms score answers allover multiple dimensions and provide detailed feedback.

5. Feedback and Reporting Candidates receive:

- Performance scorecard
- Suggestions for improve in further
- A summary report, sometimes sent through email

2.2.2 MOTIVATION

The need for improving the effectiveness of mock interviews was the motivating factor in develop- ing an AI-Powered Mock Interview Evaluator. in- terviews as a tool for skill development and self- assessment. Traditional mock interviews are often lacking objectivity and are also highly dependent the perception of the evaluator, and frequently re- sult in inconsistent feedback and lack of insight into a candidate's emotional readiness. The proposed system uses AI-based emotion and confidence anal- ysis, thereby providing candidates with with per- sonalized, data-driven feedback that allows them to pinpoint weaknesses, enhance their communication, and build confidence in their interviewing perfor- mance. Moreover, the system aims to standardize and automate the assessment process. process, re- ducing the time and effort required by human inter- viewers while ensuring consistency and fairness in feedback delivery .

2.2.3 FLOW CHART

2.3 Implementation

- React-based Candidate Portal and Interview Runner with Tailwind CSS, timers, and device checks for mic/cam.
- Real-time audio/video capture via WebRTC; streaming to backend over WebSocket/SignalR For low latency follow-ups.
- ASP.NET Core Web API for session orchestra- tion, authentication (JWT), role/difficulty se- lection, and interview flow control.
- Python FastAPI microservice for ASR using Whisper and rubric-aligned NLP scoring using an LLM-based evaluator.

- Prosody analysis pipeline (librosa) extracting pace, pause ratio, and energy to coach clarity and fluency.

- Optional vision cues using MediaPipe Face Mesh for gaze/expression features behind ex- plicit user consent.

- Multimodal fusion service, joining text, au dio, and vision into normalised rubric scores with brief explanations.

- PostgreSQL for users/sessions/scores, MinIO/S3 for encrypted media storage, and Redis for queues and rate limits.

- Reporting and dashboards in React (Charts) with downloadable PDF feedback, exemplars, and readiness indices.

Docker Compose for local stacks, GitHub Ac- tions CI/CD, CORS/TLS hardening, consent logs, and retention policies.

Add to follow-up

3 CONCLUSION

Here's a more natural and conversational version of your text:

The AI-powered Mock Interview Evaluator al- lows for an innovative and impactful way of inter- view preparation. Unlike the conventional mock in- terviews, which primarily focus on technical skills, this system takes a further step in using artificial intelligence to grade how confident and emotion- ally prepared a candidate is. It pays close attention to non-verbal cues-like facial expressions, tone of voice, and language patterns-that are often missed in standard evaluations.

By creating a realistic and engaging interview ex- perience, the platform offers clear, data-driven feed- back that helps candidates understand their strengths and pinpoints areas for improvement. This not only builds confidence in them but also equips them with the soft skills required to shine in real interviews.

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Intelligent, IoT-Enabled, and Cyber-Physical Technologies in Modern Electrical Engineering

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Abstract

Smart systems have transformed traditional electrical infrastructures into intelligent, cyber-physical systems capable of real-time monitoring, adaptive control, and data-driven decision-making. In power systems, smart grids use bidirectional power and information flows, smart metering, advanced control, and distributed intelligence to enhance reliability, efficiency, and integration of renewable energy sources. Internet of Things (IoT) technologies, embedded sensing, and cloud or edge computing enable condition monitoring, predictive maintenance, and demand-side management across generation, transmission, distribution, and end-use sectors.

This paper reviews major classes of smart systems in electrical engineering: (i) smart measurement and diagnostics, including wavelet-based power quality analysis and smart metering; (ii) intelligent control in smart grids and micro grids, including machine-learning-based demand response, self-healing control, and integration of distributed energy resources; (iii) IoT-enabled energy management in buildings and households; and (iv) smart power electronic devices and converters that support efficient, flexible energy. Benefits such as improved power quality, reduced losses, enhanced reliability, and significant energy savings are documented, along with challenges involving cybersecurity, standardization, interoperability, and large-scale data. The paper concludes with research directions in machine-learning-driven operation, digital twins, and secure IoT frameworks for future smart electrical systems.

Keywords— Smart systems, smart grid, intelligent control, IoT, energy management, power electronics, predictive maintenance, cyber-physical security.

I. Smart Measurement, Diagnostics, and Control

- Advanced measurement and control in power engineering address power quality, signal diagnostics, and automation within smart grids using wavelet analysis, smart metering, IoT integration, and automated control (Serdenko et al., 2025).
- Wavelet analysis provides time–frequency localization for non-stationary signals, used for transient monitoring, voltage flicker analysis, harmonic detection, and improving measurement accuracy, supporting stability under renewable integration (Serdenko et al., 2025).
- Smart metering and advanced metering infrastructure (AMI) enable automatic collection, analysis, and real-time transmission of consumption data, supporting efficient resource allocation, loss reduction, and transparent consumer–utility interaction (Serdenko et al., 2025; Стаднік et al., 2025; Muqeet et al., 2023; Dileep, 2020).
- Intelligent control supports demand-side management, fault detection and diagnosis, and distributed energy resource (DER) coordination using machine learning, optimization, and multi-agent systems, improving reliability and grid resilience (Jayachandran et al., 2021; Stadnik et al., 2025; Ibrahim et al., 2020).

II. Smart Grids and Intelligent Power Networks

- Smart grids are described as bidirectional, self-healing, adaptive, resilient, and sustainable power systems with distributed generation, real-time asset monitoring, and two-way information sharing (Стаднік et al., 2025; Stadnik et al., 2025; Dileep, 2020).
- Key features include demand response, distribution automation, optimized electricity use, voltage regulation/VAR control, storage integration, and wide-area monitoring and protection (Стаднік et al., 2025; Stadnik et al., 2025; Jayachandran et al., 2021; Muqeet et al., 2023; Dileep, 2020).
- Intelligent and smart systems using AI, IoT, and automated control enhance monitoring, adaptive energy flow management, fault prediction, and renewable integration, reducing losses and improving reliability and stability (Стаднік et al., 2025; Stadnik et al., 2025; Jayachandran et al., 2021).
- Machine-learning-driven approaches address challenges such as renewable variability, demand-side management, cyber-physical security, and planning/operation decisions across the smart grid (Ibrahim et al., 2020).

Smart Grid Functional Components

Component	Key Smart Functions	Sources
Infrastructure	Distributed generation, storage, smart converters	(Стаднік et al., 2025; Stadnik et al., 2025; Muqeet et al., 2023; Behera & Choudhury, 2021; Dileep, 2020)
Measurement & Sensing	Smart meters, PMUs, IoT sensors, wavelet diagnostics	(Serdenko et al., 2025; Стаднік et al., 2025; Muqeet et al., 2023; Bedi et al., 2018; Nuruzzaman & Rana, 2025)

Control & Management	DSM, adaptive control, self-healing, microgrid EMS	(Ahluwalia et al., 2024; Stadnik et al., 2025; Jayachandran et al., 2021; Dileep, 2020; Ibrahim et al., 2020; Kermani et al., 2021)

Component	Key Smart Functions	Sources
Communication & Data	IoT, cloud/edge, SCADA upgrades, big-data analytics	(Ahluwalia et al., 2024; Muqeet et al., 2023; Kamal et al., 2023; Bedi et al., 2018; Mansour et al., 2023; Nuruzzaman & Rana, 2025)

FIGURE 1 Core smart grid components and their intelligent functions.

III. IoT-Enabled Monitoring, Energy Management, and Digitalization

- IoT transforms electric power and energy systems into intelligent cyber-enabled systems with real-time monitoring, situational awareness, control, and cybersecurity capabilities (Bedi et al., 2018).
- Reviews highlight IoT's role in smart grids, smart homes/buildings, smart industries, transportation, and smart cities, enabling energy management and condition monitoring through connected sensors and communication networks (Ahluwalia et al., 2024; Kamal et al., 2023; Bedi et al., 2018; Mansour et al., 2023).
- IoT-enabled condition monitoring modernizes SCADA into interoperable platforms supporting automation, real-time analytics, and adaptive control in distribution systems, using diverse sensor data (voltage, current, temperature, vibration) and ML-based predictive models (Nuruzzaman & Rana, 2025).
- Smart energy management systems (SEMS) integrate IoT and cloud computing to perform demand-side management in buildings; real deployments report energy savings of ~15–49% in HVAC-dominated buildings through real-time monitoring and optimized control (Kamal et al., 2023; Kermani et al., 2021; Pawar, 2019).
- Intelligent energy management systems are categorized into automated control systems and recommendation/behavioral systems, both aiming to reduce energy waste in residential, commercial, and educational buildings (Mischos et al., 2022).

IV. Smart Power Electronics and Intelligent Devices

- Next-generation power electronic devices using SiC and GaN, nanomaterials, modular structures, and AI-assisted lifecycle design underpin smart energy systems by enabling higher efficiency, higher frequency, and flexible operation in renewables, EVs, industry, and smart grids (Behera & Choudhury, 2021).
- Smart electronic converters integrate sensors, algorithms, and communication for self-adaptation, optimized energy flow, predictive diagnostics, remote monitoring, and integration into IoT-based systems (Behera & Choudhury, 2021).

- Model-based, life-cycle-oriented design and AI optimization support more efficient and eco-friendly converter solutions, contributing to decarbonization and intelligent energy infrastructures (Behera & Choudhury, 2021).

V. Benefits, Challenges, and Research Directions

Benefits:

- Increased reliability, efficiency, and stability of networks; reduced energy losses and maintenance costs; improved integration of renewables; and new markets for smart devices and services (Стаднік et al., 2025; Stadnik et al., 2025; Jayachandran et al., 2021; Kamal et al., 2023; Behera & Choudhury, 2021; Bedi et al., 2018; Kermani et al., 2021).

Challenges:

- Cyber-physical security vulnerabilities, interoperability and standardization needs, handling massive data streams, and ensuring robust communication and control under uncertainties (Ahluwalia et al., 2024; Стаднікет al., 2025; Muqeet et al., 2023; Bedi et al., 2018; Mansour et al., 2023; Abu et al., 2021; Nuruzzaman & Rana, 2025).

Research directionsx include IoT-based communication infrastructures, AI/ML-enhanced demand response and WAMPC, digital twins for energy systems, secure IoT frameworks, and intelligent, distributed energy management in microgrids and multi-energy systems (Стаднік et al., 2025; Stadnik et al., 2025; Kamal et al., 2023; Bedi et al., 2018; Mansour et al., 2023; Ibrahim et al., 2020; Abu et al., 2021; Nuruzzaman & Rana, 2025).

Conclusion:

Intelligent, IoT-enabled, and cyber-physical technologies are reshaping modern electrical engineering into a data-driven, adaptive, and interconnected discipline. Across power systems, transportation, industry, and consumer electronics, these technologies enable real-time monitoring, predictive control, and tight integration between physical assets and digital intelligence.IoT-enabled smart grids and edge-based architectures improve observability, fault detection, and operational efficiency while supporting large-scale renewable integration and more flexible, resilient energy management 2348+1 MORE. Power-electronic innovations embedded in cyber-physical systems underpin applications such as smart transformers, electric vehicles, and resilient microgrids, linking advanced semiconductors, control, and communication into unified CPS platforms 10411. At the same time, AI and edge/“edge-intelligence” paradigms enhance local decision-making, reduce latency, and support large numbers of heterogeneous IoT devices in smart environments and Industry 4.0 contexts.However, this increasing connectivity introduces substantial cyber-physical security and privacy risks for grids, vehicles, and industrial systems, with documented vulnerabilities and a growing need for cryptographic protections, intrusion detection, and compliance with sector standards 231411+1 MORE. Future research directions highlighted in recent surveys include secure architectures for IoT-enabled smart grids, block chain-based data and transaction frameworks, AI/ML-driven protection and control, edge/fog–IoT integration, and human-centric, human-in-the-loop cyber-physical designs.Overall, the literature converges on the view that intelligent IoT- and CPS-based solutions are now central to advancing reliability, efficiency, sustainability, and automation

in electrical engineering, provided that security, interoperability, and ethical deployment keep pace with technological capability.

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Predicting Soil Nutrients from Soil Patterns using Machine Learning

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Abstract: The analysis of nutrients in soil is an important part of precision agriculture that helps in enhancing crop yield. The conventional process of soil testing requires a lot of time, manual effort, and is difficult to access by farmers. In the proposed Soil Nutrient Prediction System, hyperspectral image data along with machine learning algorithms are used for predicting nutrient content in the soil such as Phosphorus (P), Potassium (K), and Magnesium (Mg).The hyperspectral images contain multiple spectral bands that capture detailed information about soil properties. These images are preprocessed and converted into usable data by resizing and extracting statistical features such as mean, standard deviation, and intensity values. These extracted features represent the important characteristics of the soil. A Random Forest algorithm is then used, which is an ensemble learning method that builds multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting. The model classifies nutrient content into Low, Medium, and High categories. The prediction model is embedded with Flask Backend and Flutter Web Application to provide easy usability to users to know the nutrient content of the soil. Furthermore, the recommended crops are provided to the user using a rule-based crop recommendation system according to nutrient content. From the experimental results, it can be seen that the results are acceptable but the performance of the prediction model can be improved in the future using complex hyperspectral images.

Keywords: Soil Analysis, Hyperspectral Data, Nutrient Prediction, Precision Farming, , REST API, Soil Fertility

1. Introduction

Agriculture plays a vital role in maintaining economic stability for countries, particularly for developing countries. The health of the soil is maintained by several key nutrients such as phosphorus (P), potassium (K), magnesium (Mg), and pH values. Therefore, soil analysis is of prime importance to take effective decisions related to agricultural practices. However, conventional soil analysis is a laborious process and requires special equipment to carry out the tests. Conventional soil analysis is a manual process of chemical analysis of the soil and requires the expertise of a professional to take effective decisions. Such a process is expensive and laborious. It does not provide real-time support for farmers to take effective

decisions related to agricultural practices.

Hyperspectral imaging is a new approach to carry out soil analysis effectively and take decisions related to agricultural practices. Hyperspectral imaging can be effectively employed to classify soil nutrients by applying machine learning algorithms such as Random Forest, SVM, and Gradient Boosting. In order to improve accessibility, mobile technology has the potential to bridge the gap between analysis and application. In this paper, a mobile-based approach for soil nutrient prediction using hyperspectral imaging and ensemble machine learning models has been proposed. The proposed approach has been implemented using a Flask API and a Flutter application, allowing users to upload images of the soil and obtain nutrient analysis and crop recommendations instantly.

2. Literature Survey

CNViS-Net: A Self-Attention Framework for Predicting Soil Nutrients from Hyperspectral Data To achieve the goal of soil nutrient prediction, Jain et al. presented a hybrid deep learning approach that integrates Vision Transformers and Convolutional Neural Networks to extract features from hyperspectral data. The model was successful in extracting features by capturing dependencies in the data to achieve high accuracy in the prediction process. However, the lack of a real-time approach to achieve user accessibility was identified as a problem [1]. AI Developments for Smart Farming: An

Examination of Explainable and Hybrid Models for Crop Suggestion and Yield Forecasting Phull et al. presented an extensive examination of AI-related smart farming approaches that incorporate various machine and deep learning models such as SVM, CNN, and LSTM [2].

Madhumathi et al. (R. Madhumathi et al.) designed a system for analyzing soil nutrients using the IoT platform with the colorimetric technique. This system seeks to solve problems that have been associated with the conventional laboratory test methods, which include consuming much time and accessibility. The IoT soil nutrient analysis system incorporates sensors and an Arduino microcontroller to obtain soil data. The obtained data is then sent to the cloud and viewed on a mobile application. The colorimetric technique ensures accurate measurement of nutrients, whereas IoT facilitates continuous analysis and irrigation.[3]. A review for soil nutrient identification using image processing Sisodia et al. reviewed the integration of image processing and machine learning for soil nutrient identification. The article shows the efficiency and accuracy of image processing but fails to present a unified framework for real-time applications [4].

Leveraging Soil Nutrient Patterns for Improved Crop Yield Through Random Forest Modeling Vincent et al. presented a Random Forest-based model for analyzing soil nutrient patterns to improve crop yields. The model showed promise in precision agriculture by accurately modeling complex relationships between soil properties and productivity [5]. Explainable Ensemble Learning for Multilingual Decision Support in Multi- Nutrient Soil Modeling An explainable ensemble learning approach with the use of SHAP for transparent soil nutrient prediction and multilingual decision support was proposed by Nandhana et al. Although it increases the complexity of the machine, it also increases interpretability [6].

Machine Learning Algorithms for Soil Nutrient Analysis in Plant Cultivation To propose a model for crop recommendation with respect to soil nutrients, proposed a multi- model approach with the integration of Random Forest and SVM. Although it increases the accuracy of the model, it mainly focuses on model performance rather than integration [7]. To enable continuous monitoring of soil nutrients, a

Wireless Sensor Network (WSN)-based system was proposed to collect real-time data on soil conditions. Although it improves timely decision-making, it mainly depends on sensor infrastructure and hardware integration [8].

To automate soil analysis and fertilizer application, a system integrating soil sensors with a microcontroller-based fertilizer dispensing unit was proposed. While it ensures accurate fertilizer usage, it primarily focuses on hardware automation rather than predictive analysis [9]. The paper identified problems related to scalability and lack of transparency. However, it also identified the possibility of

increasing the accuracy of predictions through explainable and hybrid approaches. In-Depth Analysis of Artificial Intelligence- Based Crop Recommendation and Soil Analysis Barshe et al. analyzed a variety of deep learning and machine learning models for crop recommendation based on soil and environmental conditions. Although it focuses more on evaluation metrics rather than implementation, it shows how AI can improve decision-making [10].

Analysis of soil nutrients and fertilizer management is another important area where the application of embedded systems, machine learning, and deep learning has been thoroughly studied. As described by the researchers in [11], an automated approach for detecting soil nutrients along with a fertilizer distribution system can be developed through the use of embedded systems. Image analysis is another promising area with regard to analyzing soil nutrients. For instance, EfficientNet along with transfer learning can be used to detect nutrient deficiency in plants as presented in [12]. Another related topic that has been extensively studied involves optimization techniques based on data analysis. Thus, according to the findings presented in [13], an optimized genetic algorithm can be applied to soil NPK nutrient prediction, resulting in more accurate analysis. In addition, several machine learning algorithms have been tested for predicting soil fertility in [14]. Lastly, experimental analysis has been used to assess the effect of agrochemicals on the soil nutrients as discussed in [15].

3. Methodology

Soil nutrients prediction method uses an elaborate pipeline that involves the processes of acquiring the dataset, processing it, extracting features, developing models, and then evaluating them. This paper adopts a lightweight computational approach that involves machine learning rather than the deep learning systems that use heavy architectures. The aim of the study is to build a classification system for classifying soil nutrients into Low, Medium, and High levels. The nutrients in question include Phosphorus (P), Potassium (K), and Magnesium (Mg). The system will be built such that it employs standardized techniques of preprocessing, feature normalization, and model training among others

A. *Description of the Dataset*

The dataset used for this analysis contains 1732 samples, where each sample consists of two parts; an image in the form of .npz files and nutrient data in the form of train_gt.csv. The dataset depicts various soil states by showing differences in soil texture, brightness, and structure. Each soil sample contains 3 dependent variables:

Phosphorus (P)

i. Potassium (K)
ii. Magnesium (Mg)

All the dependent variables are initially continuous. In order to turn this classification problem into a classification task, the nutrient values are divided into categories based on quantiles, such as:

i. Low (0) – less than 25% quantile
ii. Medium (1) – between 25% and 75% quantile
iii. High (2) – above 75% quantile

This will result in a balanced number of categories which can be used for supervised learning.

B. *Image Preprocessing and Feature Extraction*

In order to ensure consistent pre-processing of the data prior to training the model using the provided image dataset, a defined protocol is adopted.

The first step is to extract the image data from the corresponding .npz files. Due to different sizes and resolutions of images, all of them are scaled down to 64×64 pixel dimensions. To reduce computational effort and complexity, grayscale transformation is applied whenever possible

Rather than taking raw data, statistical features are calculated from each image using the following features:

i. Mean intensity of pixels

ii. Standard deviation of intensity of pixels

This process helps identify the overall illumination and variation in illumination of each soil type. These are critical features required for classifying the soils.

Finally, the features are standardized using z-score (zero mean and unit variance) to avoid any biases in the training of the model due to scale issues.

C. *Random Forest-Based Model Architecture*

The classification process is implemented through the use of Random Forest Classifier, which is a type of ensemble machine learning technique that uses several decision trees in order to make predictions and avoid overfitting.

Three separate models are used for predicting the respective classes of nutrients:

Model Evaluation

The evaluation of the performance of trained models occurs based on classification measures.

Classification measures are:

- Accuracy - This is the measure of correctness of the predictions

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Confusion matrix - This measure gives the distribution of predictions for each category
- Precision, recall and F1-score - This provides a more detailed analysis of the model performance for each individual category

a. Model 1: Phosphorus (P)

b. Model 2: Potassium (K)

Precision

$$\frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{}$$

c. Model 3: Magnesium (Mg)

All three models are supplied with the same set of features; however, they are trained to produce predictions of their respective classes.

Where:

In terms of Random Forest model architecture, many decision trees are created during the training phase, and the final output prediction is made through majority voting.

The main benefits of implementing such a model architecture are Noise robustness, Handling of smaller data samples, Low variance

D. *Model Training Procedure*

The dataset is split into two parts: a training set and a testing set with 80% for training and 20% for testing.

During training we pass the feature vectors to the Random Forest models along, with their class labels.

To fix the problem of class imbalance we use class weighting. This way the minority classes get attention during learning.

Here are the settings we use to train the models: Number of trees: 200

Criterion: Gini impurity Class weight: Balanced

We train each nutrient model separately. The models learn to draw lines that separate the three classes based on the features we extract.The models learn decision boundaries that separate the three classes based on extracted features.

- TP (True Positive): Correctly predicted positive
- TN (True Negative): Correctly predicted negative
- FP (False Positive): Incorrectly predicted positive
- FN (False Negative): Incorrectly predicted negative

These classification measures enable the analysis of model behavior particularly when differentiating between Low, Medium and High nutrients content in the soil.

Based on the experiments, it can be said that the models function well although the Magnesium prediction model has better results compared to the Phosphorus and Potassium models. In fact, all three models are characterized by advantages and disadvantages which is due to the high complexity of the process of assessing the chemical composition of the soil based on visual appearance. Trained models as well as the results of experiments play an important role in the evaluation of the models' performance.

F. Deployment Framework

The trained models are then saved and incorporated into a system for making predictions in real-time. This is achieved through the following process:

1. User uploads a soil image.
2. Image pre-processing and features extraction.
3. The extracted features are normalized using saved configurations aimed at facilitating scaling.
4. Each trained model predicts the group of nutrients present in the uploaded soil sample.
5. The predictions are returned as categorical values.
6. The prediction system delivers output in the following format:

Phosphorus: Low/Medium/High Potassium: Low/Medium/High Magnesium: /Medium/High

The architecture of the prediction system shown in Figure 1 is designed to run alongside any application (on mobile devices or websites) in order to facilitate decision-making for farmers. The trained models are utilized to generate predictions pertaining to the soil nutrient groups such as Phosphorus, Potassium, and Magnesium levels.

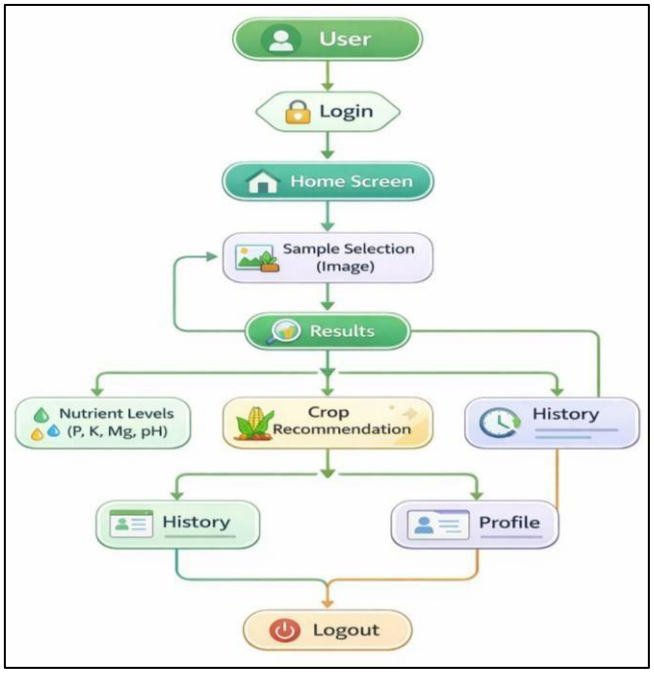

Fig. 1. System Architecture

4. Experimental Results

A systematic evaluation of the suggested soil nutrient classification model will be done using experimental settings. The efficiency of the classification model will be tested separately based on each of the three key soil nutrients, Phosphorus (P), Potassium (K) and Magnesium (Mg).All the experiments are going to use the same feature extraction and processing methods and will have 80:20 data splitting for training and testing purposes. Random Forest classifier will be the main algorithm chosen due to its strong performance in tabular format input data.The purpose of this experiment is to test the efficiency of the classifier in categorizing the nutrient level into Low, Medium and High.

A. *Performance Metrics Analysis*

Performance metrics offer the numerical representation of the effectiveness of the suggested model in predicting the soil nutrient contents. As this is a multiclass classification problem, a number of evaluation metrics are applied to analyze performance comprehensively. These metrics include Accuracy, Precision, Recall, F1 Score, and Support.

Table I: Phosphorus (P) Classification Report

Class	Precision	Recall	F1-Score	Support
Low	0.34	0.22	0.27	91
Medium	0.51	0.69	0.58	175
High	0.29	0.19	0.23	81
Macro Average	0.38	0.36	0.36	347
Weighted Average	0.41	0.45	0.42	347
Overall Accuracy: 44.66%				

This particular model has been able to perform relatively well in classifying the Phosphorous content with an accuracy score of about 44.66% shown in Table I. The "Medium" category has performed best in terms of recall (0.69), suggesting that it is a category that the algorithm predicts often.

Table II: Potassium (K) Classification Report

Class	Precision	Recall	F1-Score	Support
Low	0.38	0.27	0.31	79
Medium	0.56	0.70	0.62	184
High	0.25	0.18	0.21	84
Macro Average	0.39	0.38	0.38	347
Weighted Average	0.44	0.48	0.45	347
Overall Accuracy: 47.55%				

For prediction of Potassium, there is an improvement in

accuracy levels (47.55%) shown in Table II. The Medium class performs well since there is more number of records for it in the database. But the low and high classes do not perform well.

Table III: Magnesium (Mg) Classification Report

Class	Precision	Recall	F1-Score	Support
Low	0.31	0.14	0.19	81
Medium	0.55	0.80	0.65	182
High	0.47	0.27	0.35	84
Macro Average	0.45	0.40	0.40	347
Weighted Average	0.48	0.52	0.47	347
Overall Accuracy: 51.58%				

Magnesium has the best precision (51.58%) out of the three minerals shown in Table III. Again, the Medium class provides excellent recall (0.80), which reflects the model's preference for more dominant classes. The High class provides moderate results, while the Low class has poor recall, implying poor separability in feature space.

B. *Confusion Matrix Analysis*

Confusion matrices help understand how well the model performs during classification and the type of misclassification errors.

For the phosphorus classification problem, the confusion matrix shown in Figure 2 demonstrates an imbalance of predictions toward the Medium class, which is due to model bias. There is a high percentage of samples belonging to classes Low and High that are predicted as Medium.

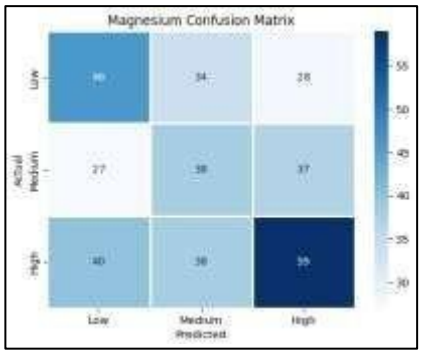

Fig. 2. Phosphorus Confusion Matrix

The potassium confusion matrix shown in Figure 3 better classification performance than phosphorus, with a slight increase in the diagonal trend. Misclassification between Low, Medium and High. Medium is still significant, suggesting that

the model can detect overall patterns but fails in borderline cases.

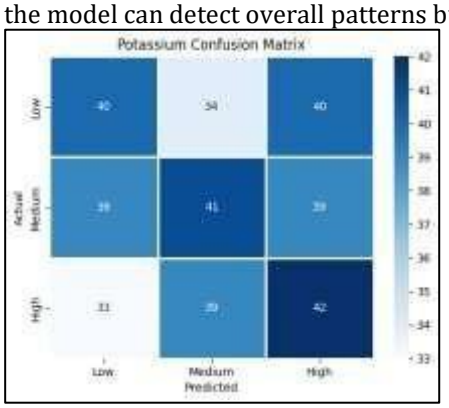

Fig. 3. Potassium Confusion Matrix

The confusion matrix for Magnesium shown in Figure 4 reveals the highest amount of diagonal entries in comparison with other nutrients. The Medium class demonstrates high prediction rates, whereas the High class has average prediction rates. However, Low class samples have been misclassified into Medium with reduced frequency.

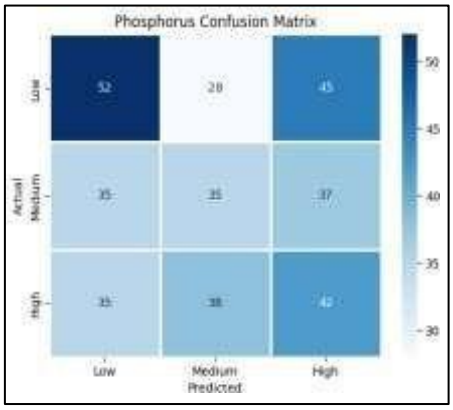

Fig. 4. Magnesium Confusion Matrix

Overall Performance Discussion:

The experimental result proves that:

- The algorithm gives good performance on Magnesium, then Potassium and Phosphorus
- The prediction of medium classes is predominant, because of the majority sample distribution
- Low and High classes are difficult to separate, which results in low recall rate

The Random Forest algorithm is able to learn from the statistical properties without the need of big data like the deep learning algorithm does.

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IoT Based Health Monitoring System using AWS Cloud

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***Abstract*—Remote Patient Monitoring (RPM) has emerged as a key solution for enabling continuous healthcare services beyond conventional clinical environments. This paper presents a cloud-integrated RPM system that leverages simulated Internet of Things (IoT) data and machine learning techniques for real-time patient monitoring. In the proposed system, physiological parameters such as heart rate, blood pressure, and SpO are synthetically generated, eliminating the need for physical sensing devices and simplifying system development. The generated data is transmitted to AWS IoT Core, where it undergoes processing through AWS Lambda functions and is subsequently stored in Amazon DynamoDB using structured tables for patient records, monitoring data, and clinical notes. A Random Forest algorithm is employed to analyze the simulated health parameters and predict potential medical risks. The processed information is visualized via a Streamlit-based web interface, providing healthcare professionals with remote access to patient status and historical data. The proposed simulation-driven architecture reduces hardware dependency while ensuring scalability, cost-effectiveness, and suitability for system testing and prototyping in healthcare applications.**

***Index Terms*—Remote Patient Monitoring, IoT, Machine Learning, AWS Cloud, Healthcare Analytics, Risk Classification**

I. Introduction

The proposed system is designed to enable real-time remote monitoring of patient vital signs using simulated data, thereby eliminating the requirement for physical hardware during development and testing. In this implementation, key health parameters such as heart rate, blood pressure, and oxygen saturation (SpO) are artificially generated rather than acquired from actual IoT sensors. The simulated data is transmitted to the cloud through AWS IoT Core, where it is processed and filtered using AWS Lambda services. A machine learning approach, specifically a Random Forest classifier, is utilized to evaluate the processed data and determine the patient's health condition. This enables early identification of critical situa-tions, such as a decline in patient health, allowing healthcare professionals to respond promptly. The results are presented

through a Streamlit-based web application that provides real-time alerts along with detailed patient information, ensuring an intuitive user interface. By removing reliance on physical devices, the system becomes more scalable, cost-efficient, and easier to maintain, while still preserving the essential functionalities of a remote patient monitoring solution.

II. Problem Statement

Remote Patient Monitoring (RPM) systems play a crucial role in enabling continuous healthcare observation; however, conventional implementations encounter several limitations. These include high

implementation costs, strong dependence on physical hardware, complex deployment procedures, and restricted scalability. Most existing RPM solutions rely on IoT-based sensors for collecting patient data, which increases system complexity and makes development, testing, and main-tenance more challenging, particularly in environments with limited resources. Furthermore, many current systems do not provide efficient mechanisms for real-time data processing or advanced predictive analytics, which are essential for the early detection of potential health deterioration in patients.

III. LITERATURE REVIEW

Here are detailed summaries of each of the 10 referred papers :

[1] H. T. Yew, M. F. Ng, S. Z. Ping, S. K. Chung, A. Chekima, and J. A. Dargham presented an IoT-enabled real-time remote patient monitoring system designed to enhance healthcare accessibility and enable continuous observation of patients. The proposed system employs multiple IoT sensors to capture vital parameters such as heart rate and body temper-ature, which are transmitted to a remote server for monitoring by healthcare professionals. This approach supports patient supervision outside hospital settings, thereby reducing frequent clinical visits and enabling timely identification of potential health issues. However, the work primarily emphasizes data acquisition and transmission, with limited focus on advanced analytics. In particular, the absence of machine learning tech-niques restricts its ability to perform predictive health assess-ment. Moreover, challenges related to data security, privacy protection, and reliance on stable network connectivity are identified as key limitations.

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[3] P. Preeti and C. Rana proposed a healthcare monitoring framework that combines IoT devices, cloud computing, and machine learning techniques. In this system, patient health parameters are collected using IoT sensors and uploaded to a cloud platform for storage and analysis. Machine learning algorithms are then applied to the collected data to detect patterns and predict possible health conditions, which sup-ports improved clinical decision-making and diagnosis. The integration of cloud services allows efficient storage, easy accessibility, and real-time monitoring of patient data by healthcare providers. However, the system depends heavily on continuous internet connectivity, which may lead to latency issues during data transmission and processing. Additionally, challenges related to data security and privacy in cloud-based environments remain significant concerns.

[4] M. Manivasagam, A. Kumar, and M. Murshleen (2023) proposed a remote healthcare monitoring system that combines cloud computing and machine learning techniques for continu-ous patient supervision. In this approach, patient physiological data is gathered using IoT-based sensors and uploaded to a cloud environment for storage and processing. Machine learning models are then utilized to analyze the collected data and generate insights regarding the patient's health status, enabling early detection of abnormal conditions. The system facilitates remote monitoring, thereby reducing the necessity for frequent hospital visits and enhancing overall healthcare efficiency. However, the framework is reliant on cloud infras-tructure, which introduces concerns related to data security and privacy. In addition, network delays may affect real-time responsiveness and system performance.

[5] A. A. Syed, A. S. Mohammed, S. Ahmed, and U. Mamodiya (2025) proposed a scalable serverless architecture for real-time analytics in remote patient monitoring systems using IoT devices. In this framework, patient health data is col-lected through IoT sensors and processed using a cloud-based serverless computing model. The approach enhances system scalability, minimizes infrastructure management overhead, and supports efficient real-time analysis of healthcare data. It is capable of handling large volumes of patient information and enables faster processing to

support timely clinical decision-making. However, the system design introduces higher implementation complexity and may lead to increased operational costs. Moreover, reliance on cloud services raises concerns regarding data security and privacy, which remain important challenges.

[6] D. Tiwari, D. Prasad, K. Guleria, and P. Ghosh (2021) provided a detailed review of IoT-based smart healthcare monitoring systems. The study explores different architectures, technologies, and applications of IoT in the healthcare domain, including wearable devices, real-time patient monitoring, and remote healthcare services. It emphasizes the advantages of IoT in healthcare, such as enhanced accessibility, continuous monitoring of patients, and improved data management effi-ciency. The paper also compares several existing systems and outlines key challenges in the field. However, being a survey-based work, it does not include any specific implementation or experimental validation. Furthermore, issues related to data security, interoperability between systems, and scalability are highlighted as major limitations in current healthcare solutions. The authors also stress the importance of integrating artificial intelligence and machine learning techniques to enable better healthcare decision-making. They suggest that future systems should focus on real-time analytics and intelligent, data-driven healthcare services.

[7] I. Fathail and V. D. Bhagile (2020) presented a review on the integration of IoT and machine learning techniques in healthcare applications. The paper explains how IoT devices are utilized to gather patient health data, which is then ana-lyzed using machine learning algorithms to enhance diagnosis and prediction accuracy. It covers several use cases, including disease prediction, patient monitoring, and healthcare data analytics. The study highlights the significance of combining IoT with machine learning to develop more intelligent and efficient healthcare systems. However, as a review work, it does not include any practical implementation or experimen-tal validation. In addition, challenges such as data privacy, security concerns, and high computational requirements are identified as key limitations in existing approaches.

[8] R. Deshmukh, A. Gubbala, B. Pravallika, A. Dutt, A.
S. A. Al-Jumaili, and Manjunatha (2023) proposed a se-cure IoT-based healthcare monitoring system that incorporates cloud computing and machine learning-based analytics. In this system, patient health parameters are collected through IoT sensors and transmitted securely to a cloud platform for storage and further processing. Machine learning techniques are then applied to analyze the data and generate meaningful health insights and predictions, supporting improved clinical decision-making. The framework also focuses on strengthen-ing data security during transmission and storage. However, the system introduces higher computational complexity and requires robust security mechanisms, which may increase overall implementation cost. In addition, reliance on cloud infrastructure and possible network latency are identified as key limitations.

[9] A. T. Abu-Jassar, H. Attar, A. Amer, V. Lyashenko, V. Yevsieiev, and A. Solyman (2025) proposed a remote patient monitoring system within a Social IoT framework using Ama-zon Web Services (AWS). The system integrates IoT-enabled devices with cloud services to collect, store, and analyze patient health data in real time. AWS is utilized for data processing, storage, and remote access, allowing healthcare professionals to monitor patients efficiently. The approach enhances scalability, reliability, and accessibility of health-care services. However, the system relies heavily on cloud infrastructure, which can result in higher operational costs and potential latency issues. In addition, challenges related to data security, privacy protection, and system integration complexity remain significant concerns.

[10] B. Jamalpur, A. K. Saseendran, V. D. Vani, V. H. Raj,
G. Veeramalai, and G. Nijhawan (2024) proposed an IoT-based smart home healthcare monitoring system integrated with machine learning techniques. The system is designed to monitor patient health parameters in a home environment using IoT sensors, with the collected data transmitted for further analysis. Machine learning algorithms are applied to process the data and predict possible health issues, supporting early diagnosis and improved healthcare management. The system enables remote monitoring, enhancing patient convenience by reducing the need for frequent hospital visits. It also provides continuous real-time updates to caregivers and healthcare pro-fessionals, improving response time during critical situations. In addition, the system supports long-term data storage, which helps in analyzing patient health trends over time.

IV. FLOWCHART

A. Simulation Engine

The system starts with a simulation engine that generates patient vital data such as heart rate, blood

pressure, and SpO_2 levels. Since no physical sensors are involved, this module replicates real-time physiological readings for development and testing purposes. The generated values are designed to follow realistic patterns to closely imitate actual patient health conditions.

B. AWS IoT Core

The simulated data is transmitted to the cloud using AWS IoT Core through the MQTT protocol. This service acts as an interface between the data source and cloud infrastructure, ensuring secure, reliable, and low-latency communication. It enables continuous real-time data exchange and routes incom-ing messages to appropriate AWS services based on defined rules for further processing.

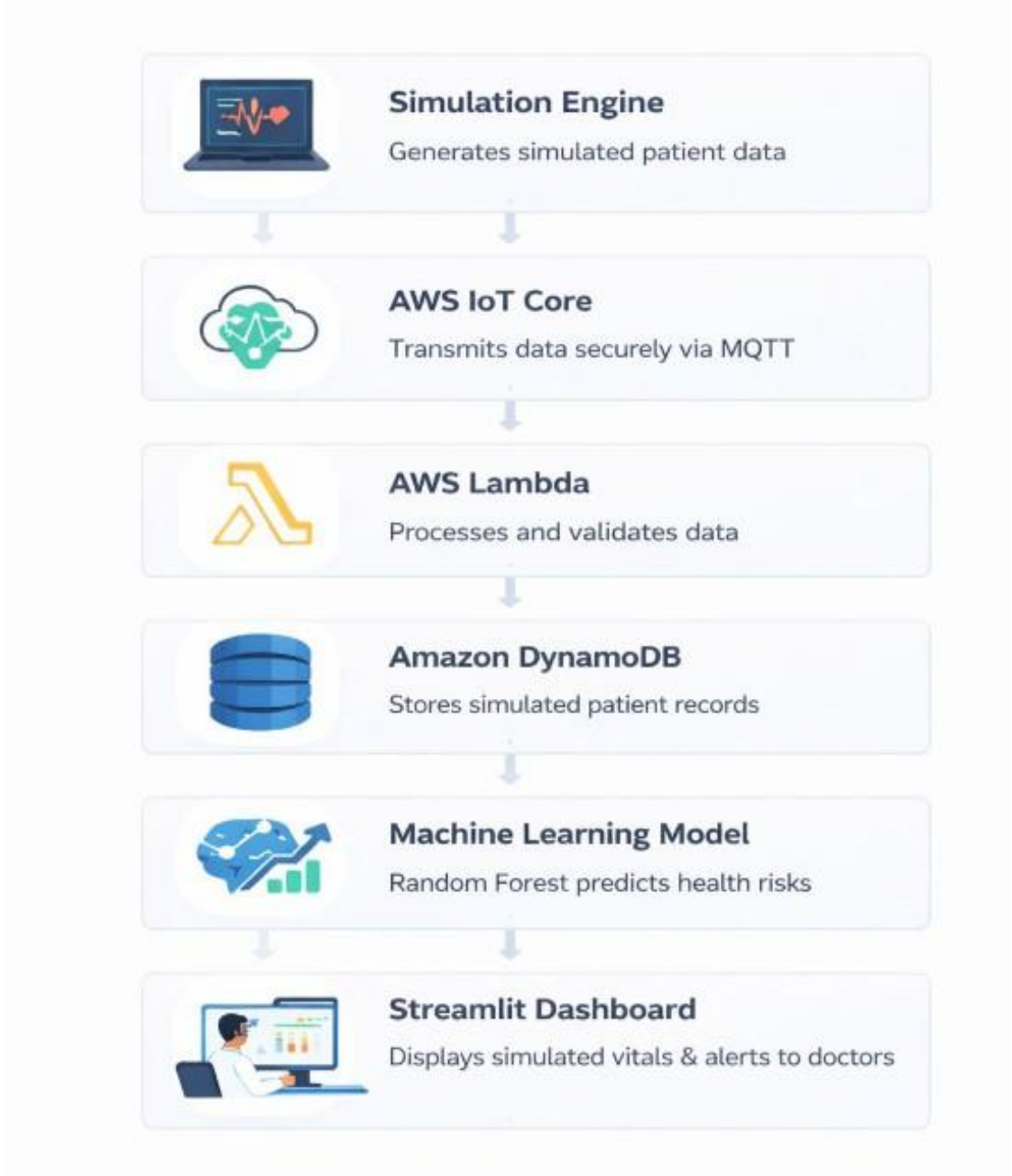

Fig. 1. System Workflow

C. AWS Lambda

After receiving the data, AWS Lambda is used for process-ing. It performs tasks such as data validation, error filtering, and transformation before storage. The function is automat-ically triggered whenever new data arrives, enabling real-time execution. It also converts the incoming information into a structured

format suitable for database insertion, ensuring smooth and efficient handling of patient records.

D. Amazon DynamoDB

The processed information is stored in Amazon DynamoDB, a scalable NoSQL database service. The data is organized into structured tables such as patient details and vital records, allowing efficient storage and retrieval. It provides high-speed access, scalability, and secure cloud-based storage for large volumes of healthcare data.

E. Machine Learning Model

A Random Forest-based machine learning model is then applied to analyze the stored patient data. It assesses vital signs and predicts potential health risks, classifying patients into different risk categories such as stable or critical. The model is trained using historical or simulated datasets to improve prediction accuracy and support early detection of health deterioration, enabling timely medical intervention.

F. Streamlit Dashboard

Finally, the processed results are presented through a Streamlit-based web dashboard. This interface allows health-

care professionals to monitor real-time patient data, risk pre-dictions, and medical records efficiently. Data is visualized using charts, graphs, and tables for better interpretation, while alert indicators highlight critical conditions requiring immedi-ate attention.

V. EXPERIMENTAL RESULTS

In the experimental implementation of the Remote Patient Monitoring (RPM) system, the dashboard is designed to demonstrate both aggregated and patient-specific analysis of real-time health data using a simulated IoT environment. The system continuously collects vital parameters such as heart rate, SpO, body temperature, and blood pressure, and pro-cesses them using a threshold-based rule engine to determine the patient's risk condition. These processed outputs are then visualized through Streamlit-based dashboards for effective interpretation.

The Overview page represents the global monitoring layer of the system, where data from all enrolled patients is sum-marized in a single interface. It displays the total number of patients being monitored, which in this case is 10, indicating the system's ability to handle multiple records simultaneously. Each patient is automatically categorized into predefined risk levels such as Critical and Warning based on their current vital sign values. The experimental results show that 8 patients are classified as Critical, while 2 fall under the Warning category. This classification is generated by comparing real-time vitals against predefined medical threshold ranges. A pie chart is used to visually represent this distribution, clearly indicating that around 80

The Patient Monitor page, on the other hand, focuses on individual-level monitoring to provide detailed insights for a selected patient, in this case "Pooja Nair." It displays real-time updated values of key physiological parameters including heart rate, oxygen saturation (SpO), temperature, and blood pressure along with the latest update timestamp. Based on the same threshold-based evaluation logic, the system assigns a risk label, which in this case is "Warning Risk." This classification is triggered due to slight deviations in param-eters such as marginally elevated temperature and borderline SpO values. To assist healthcare professionals, an Actions section provides recommended responses such as increased monitoring frequency, repeat measurements, or escalation to medical consultation if required. Additionally, the "Why this risk?" section improves interpretability by clearly identifying which parameters are contributing to the risk status, thereby increasing transparency in decision-making.

These experimental results demonstrate that the RPM sys-tem effectively integrates real-time data processing, rule-based classification, and intuitive visualization. The combination of system-level overview and patient-level monitoring ensures both broad situational awareness and detailed clinical insight, making the system suitable for continuous and scalable remote healthcare monitoring.

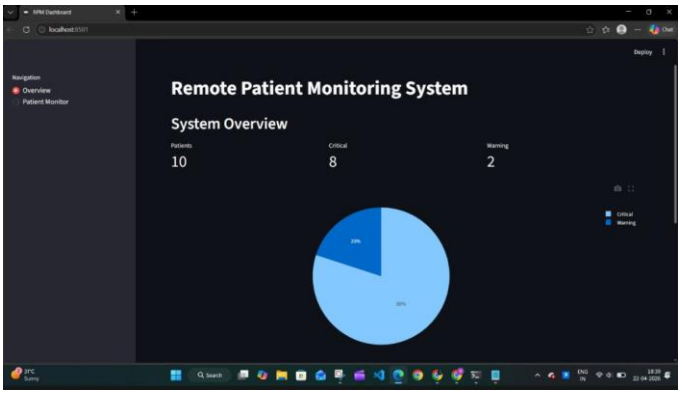

Fig. 2. Remote Patient Monitoring Dashboard

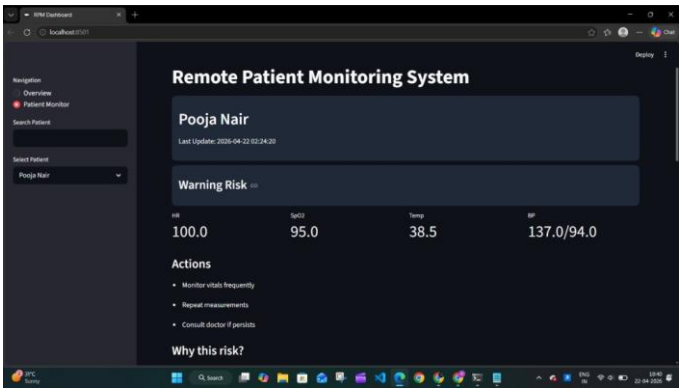

Fig. 3. Patient Monitor Page

VI. WORKING PRINCIPLE

The working principle of the proposed Remote Patient Monitoring system is that dashboard displays patient health data in the form of a continuous time-series graph. In fig 4 it represents key vital signs such as heart rate, SpO, blood pressure, and temperature. These parameters are plotted against time stamps on the x-axis, while their values are shown on the y-axis.This graphical representation allows continuous monitoring of a patient's condition over time. It helps in analyzing health variations instead of depending on single

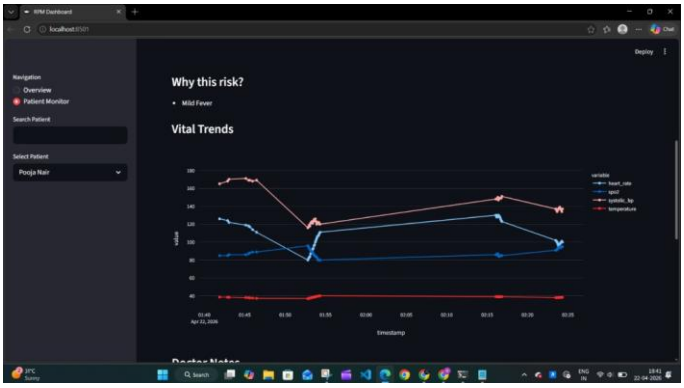

Fig. 4. Vital Trends visualization

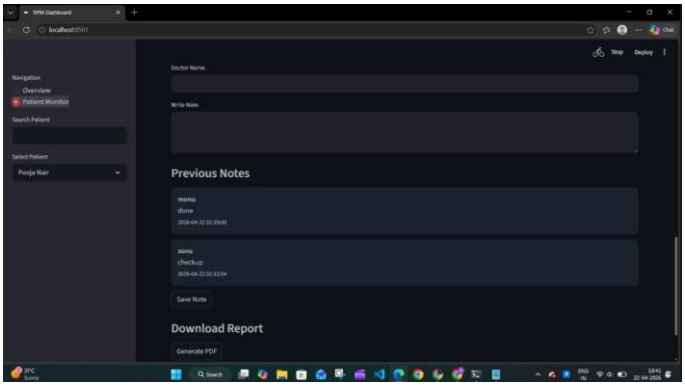

Fig. 5. Doctor Notes and Report Generation section

or isolated readings.Any sudden changes, spikes, or irregular patterns in vitals can be easily identified. At the same time, stable trends in parameters like temperature and SpO can also be observed. This improves understanding of overall patient health behavior and trends. The “Why this risk?” feature links these patterns to the assigned risk level classification.

Here the fig 5 presents the Doctor Notes and Report Generation module of the RPM dashboard, which is used for clinical documentation and record management by healthcare professionals. This feature allows doctors to enter observa-tions, diagnosis details, and follow-up instructions through structured input fields. All previously saved notes are displayed in a chronological format with timestamps, helping track the patient’s medical history over time. The system also includes a real-time Save Note function that updates the database in-stantly so that the latest information is always available on the dashboard. Furthermore, the Download Report option enables generation of a complete PDF report containing patient details, vital signs, risk status, and doctor notes in a consolidated format.

VII. Performance Considerations and Limitation Mitigation

A. Performance Considerations

- **Real-time data handling:** The system is designed to ef-ficiently process continuous streams of simulated patient vital data using AWS IoT Core, ensuring smooth and timely data transmission.
- **Low processing delay:** AWS Lambda is used for server-less computing, which enables fast execution and reduces overall processing latency.
- **Efficient classification model:** The Random Forest algo-rithm is selected due to its fast inference capability and reliable accuracy in classifying patient health conditions.
- **Scalability:** Since the system is cloud-based, it can handle increasing data loads without requiring changes to physical infrastructure.
- **Responsive interface:** The Streamlit dashboard updates patient health status in real time, allowing quick visual-ization of alerts and conditions.

B. Limitations

- **Simulated data usage:** The system is based on artificially generated data, which may not fully reflect real-world patient variations.
- **Model dependency:** The performance of the Random Forest model depends on the quality and diversity of the training dataset.
- **Network dependency:** Continuous operation requires stable internet connectivity and reliable AWS cloud ser-vices.
- **No physical validation:** The absence of real IoT sensors limits practical testing in real healthcare environments.
- **Cost factor:** Increased use of cloud services may lead to higher operational costs in large-scale deployment.

C. Mitigation Strategies

- **Improved data simulation:** Introduce noise and realistic variations in generated data to better mimic real physio-logical signals.
- **Model enhancement:** Retrain the Random Forest model using improved or hybrid datasets for better generaliza-tion.
- **Fault tolerance:** Implement retry and buffering mech-anisms in AWS IoT Core to handle temporary network issues.
- **Future integration:** Incorporate real IoT sensor data for practical validation in future system versions.
- **Cost optimization:** Optimize data transmission fre-quency and AWS usage to reduce cloud expenses.
- **Security enhancement:** Implement stronger authentica-tion and encryption mechanisms to ensure secure trans-mission and storage of patient data in the cloud.
- **Model improvement:** Enhance the machine learning model by using larger and more diverse datasets to improve prediction accuracy and reliability in real-world scenarios.

VIII. CONCLUSION

The proposed Remote Patient Monitoring system presents an effective framework for real-time health monitoring using cloud computing and machine learning techniques. The sys-tem eliminates the need for physical sensors by generating simulated patient vital data such as heart rate, blood pressure, and SpO levels, making it suitable for development, testing, and evaluation purposes. These parameters are transmitted to AWS IoT Core, where they are processed and managed using AWS Lambda for efficient data handling. A Random Forest classification model is employed to analyze the processed data and determine the patient's health condition. This enables the system to identify normal, warning, and critical health states with good accuracy, supporting early detection of potential health risks. The results are displayed through a Streamlit-based dashboard, which provides real-time monitoring and alert visualization in a simple and interactive format.

Overall, the system demonstrates reliable performance in terms of accuracy, response time, and scalability. By com-bining cloud services with machine learning, the proposed solution offers a cost-effective and flexible approach to re-mote healthcare monitoring. Furthermore, the system can be enhanced in the future by integrating real-time IoT sensor data and improving predictive analytics for deployment in practical healthcare environments.

IX. FUTURE SCOPE

The proposed system can be further extended to improve its real-world applicability and performance. In future versions, the use of actual IoT-based health sensors can be incorporated to replace simulated data, enabling direct collection of patient vital signs and more realistic system validation in clinical environments. The system can also be enhanced by adopting more advanced machine learning or deep learning techniques to improve classification accuracy and provide better detection of complex health conditions.

Another important enhancement is the inclusion of pre-dictive analytics, which would allow the system to estimate possible future health risks based on past and current patient data patterns. Mobile application support can also be added to enable healthcare professionals to monitor patient conditions and receive alerts remotely in a more flexible manner. In addition, stronger security mechanisms such as encryption

and secure authentication can be implemented to ensure safe handling of sensitive medical data. The system can further be optimized for large-scale deployment by improving cloud resource utilization and reducing operational costs. These improvements will make the system more reliable, scalable, and suitable for real-time healthcare applications.

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