Proact Secure: An AI and IoT-Based Intelligent Real-Time Safety Monitoring and Alert System

1Aboosalih Kakkat Chalil , 2Sahasra Reddy Gongula, 3Gurram Dheeraj Reddy, 4Neerudu Vinay
1Assistant Professor, 234Students
Sreenidhi Institute of Science and Technology , Yamnapet, Hyderabad
abswalih@gmail.com , sahasrareddygongula@gmail.com , gurramdheerajreddy1@gmail.com , vinayneerudu199@gmail.com

Abstract
Proact Secure is an advanced smart safety system developed to enhance real-time monitoring and rapid alert generation across environments such as industrial workplaces, educational institutions, and public areas. The system integrates Internet of Things (IoT) sensors, computer vision techniques, and artificial intelligence (AI) algorithms to continuously observe environmental conditions, detect abnormal activities, and identify potential threats. Unlike traditional monitoring approaches that rely on manual supervision and delayed responses, Proact Secure employs automated data analysis and edge computing to ensure faster detection and instant notification through multiple communication channels. The system not only reacts to incidents but also supports predictive analysis to prevent hazards before they occur, thereby improving overall safety and operational efficiency. Its scalable and adaptable architecture allows deployment across various domains while minimizing human dependency and latency issues. By combining intelligent analytics with real-time communication, Proact Secure establishes a proactive, reliable, and efficient safety management framework.

I.Introduction

In recent years, ensuring safety and security across industrial, institutional, and public environments has become a major challenge due to increasing complexity, population density, and technological expansion. Traditional safety systems, which rely primarily on manual monitoring and delayed response mechanisms, are often inadequate in addressing real-time threats such as unauthorized access, accidents, fire hazards, and abnormal human activities. These limitations have led to the emergence of intelligent monitoring systems that leverage advanced technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) to enhance situational awareness and enable proactive safety management [1][2].

The rapid growth of IoT has enabled the deployment of interconnected sensors capable of continuously collecting environmental and operational data such as temperature, gas levels, motion, and occupancy. These sensors facilitate real-time data acquisition and transmission, forming the backbone of smart safety systems [3][4]. However, raw sensor data alone is insufficient without intelligent processing. This is where AI and ML techniques play a crucial role by analyzing large volumes of data to identify patterns, detect anomalies, and make predictive decisions [5][6]. Computer vision, a subset of AI, further enhances monitoring capabilities by enabling automated visual surveillance through cameras, reducing the need for constant human supervision [7].

Existing safety systems predominantly operate on reactive mechanisms, where actions are taken only after an incident occurs. Such approaches result in delayed emergency responses, increased risk, and potential damage to life and property [8]. Moreover, many systems rely heavily on cloud-based processing, which introduces latency and dependency on stable network connectivity, making them less reliable during critical situations [9]. The lack of integration between IoT devices and intelligent analytics further limits their effectiveness in real-time applications [10].

To overcome these challenges, modern smart safety solutions are increasingly adopting edge computing, which allows data processing closer to the source, thereby reducing latency and enabling faster decision-making [11]. Additionally, integrating AI-driven analytics with IoT infrastructure enables continuous monitoring, automated alert generation, and predictive risk

assessment, significantly improving response time and efficiency [12]. These advancements have paved the way for the development of intelligent systems that not only detect hazards but also anticipate and prevent them.

In this context, the proposed system, Proact Secure, is designed as an AI- and IoT-based intelligent monitoring solution that provides real-time safety alerts and proactive risk management. The system integrates smart sensors, cameras, and machine learning algorithms to continuously monitor environments, detect anomalies, and instantly notify concerned authorities. By combining automation with real-time analytics, the system minimizes human intervention and enhances overall safety performance. Its scalable and adaptable architecture makes it suitable for diverse applications including smart cities, industries, healthcare, and educational institutions [13][14][15].

II.Literature Survey

The rapid advancement of intelligent monitoring systems has led to extensive research in the fields of Internet of Things (IoT), Artificial Intelligence (AI), and anomaly detection for safety applications. Early studies primarily focused on the development of IoT-based monitoring systems that utilize interconnected sensors to collect environmental and operational data. These systems improved real-time data acquisition and enabled remote monitoring; however, they lacked intelligent decision-making capabilities and relied heavily on manual analysis [1].

With the evolution of machine learning techniques, researchers began integrating AI algorithms into IoT systems to enhance anomaly detection and predictive analysis. Studies have shown that machine learning and deep learning models, such as supervised and unsupervised learning approaches, are highly effective in identifying abnormal patterns in sensor data and improving system reliability [2]. In particular, anomaly detection has become a critical component in IoT systems, as it helps identify deviations from normal behavior, enabling early detection of faults, intrusions, or hazardous situations .

Recent research has emphasized AIoT (Artificial Intelligence of Things), which combines IoT infrastructure with AI-based analytics for intelligent surveillance and monitoring. For instance, hybrid deep learning models using convolutional neural networks (CNN) and recurrent architectures have been proposed for real-time anomaly detection in surveillance systems. These models extract features from video data and analyze temporal patterns to detect unusual activities with high accuracy . Such approaches significantly reduce human intervention and improve the efficiency of monitoring systems.

In addition, several studies have explored the application of smart surveillance systems in different domains such as smart cities, healthcare, and home environments. AI-powered surveillance systems can automatically detect suspicious activities, reduce human error, and provide real-time alerts, thereby enhancing overall security and safety . In healthcare IoT, advanced models such as Hidden Markov Models (HMM) and Support Vector Machines (SVM) have been used to detect anomalies in patient data, ensuring timely intervention and improved patient safety .

Furthermore, recent survey papers highlight the importance of scalable and efficient anomaly detection techniques in IoT environments. These studies categorize detection methods into statistical, machine learning, and deep learning approaches, and identify challenges such as data heterogeneity, lack of labeled datasets, and system integration issues . Another key development is the adoption of edge computing, which allows data processing closer to the source, reducing latency and improving real-time response in safety-critical applications.

Despite these advancements, existing systems still face limitations such as high computational requirements, dependency on cloud infrastructure, and difficulty in handling dynamic environments. Additionally, integrating multiple technologies such as IoT sensors, AI models, and real-time communication systems remains a challenge. Therefore, there is a need for a unified, scalable, and efficient intelligent monitoring system that can provide real-time alerts, predictive analysis, and reliable performance across various domains.

The proposed system, Proact Secure, builds upon these research advancements by integrating IoT, AI,

computer vision, and edge computing to create a comprehensive real-time safety monitoring solution. It addresses existing gaps by providing automated detection, faster response, reduced latency, and proactive risk management, making it suitable for modern smart environments.

III.Proposed Methodology

The proposed system**,** Proact Secure, is designed as an intelligent real-time safety monitoring framework that integrates Internet of Things (IoT), Artificial Intelligence (AI), computer vision, and edge computing to provide proactive hazard detection and instant alert generation. The system follows a layered architecture consisting of sensing, processing, communication, and application layers to ensure efficient and scalable operation.

In the first stage, the **data acquisition layer** consists of multiple IoT-enabled sensors and surveillance cameras deployed across the monitoring environment. These sensors continuously collect real-time data such as temperature, gas levels, motion, light intensity, and human activity. Cameras capture live video streams, enabling visual monitoring. This layer ensures continuous environmental awareness and forms the foundation for intelligent analysis.

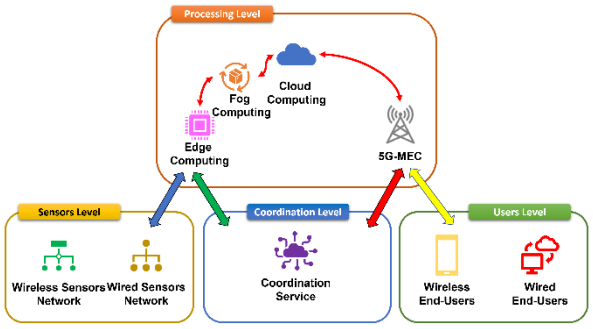
In the second stage, the collected data is forwarded to the edge processing layer, where initial filtering and preprocessing take place. Edge devices such as microcontrollers or embedded systems process data locally to reduce latency and network dependency. Computer vision algorithms are applied to video streams to detect unusual human behavior, unauthorized access, or suspicious movements. Simultaneously, sensor data is cleaned and structured for further analysis.

The third stage involves the AI and analytics layer**,** where machine learning models analyze the processed data to detect anomalies and predict potential risks. These models are trained to recognize normal patterns and identify deviations that may indicate unsafe conditions such as fire hazards, gas leaks, or abnormal activities. Predictive analytics enables the system to anticipate risks before they escalate, making the approach proactive rather than reactive.

In the fourth stage, the system utilizes the **communication layer** to transmit alerts and data through reliable channels such as Wi-Fi, GSM, or cloud-based platforms. When an anomaly is detected, the system generates real-time alerts and sends notifications to users, administrators, or emergency services via mobile applications, SMS, or web dashboards. This ensures rapid response and improved decision-making during critical situations.

Finally, the **application layer** provides an interactive interface for users to monitor system status, view live data, and receive alerts. A web or mobile-based dashboard displays sensor readings, video feeds, and system analytics in real time. Additionally, the system supports data storage for future analysis and system optimization. The integration of all these layers ensures continuous monitoring, automated detection, and efficient emergency response.

IV.Architecture Diagram Explanation



The architecture of the proposed system follows a structured flow:

- **Sensors & Cameras Layer:** Collects environmental and visual data in real time.
- **Edge Processing Unit:** Performs local data filtering, preprocessing, and quick decision-making to reduce latency.
- **AI & Analytics Engine:** Applies machine learning and computer vision for anomaly detection and predictive analysis.
- **Cloud/Server Layer:** Stores data, supports large-scale processing, and ensures system scalability.
- **User Interface & Alert System:** Delivers real-time alerts and provides monitoring dashboards for users.

This layered architecture ensures low latency, high accuracy, scalability, and reliability, making the system suitable for smart cities, industries, healthcare, and public safety applications.

V.Experimental Results and Evaluation

The performance of the proposed **Proact Secure** system was evaluated using a prototype implementation consisting of IoT sensors (temperature, gas, motion), surveillance cameras, and an edge computing unit integrated with AI-based anomaly detection models. The system was tested in a controlled indoor environment simulating real-world scenarios such as unauthorized access, abnormal movement, and hazardous environmental conditions.

During experimentation, multiple datasets were generated from sensor readings and video streams. The AI model was trained using labeled data representing normal and abnormal conditions. Performance evaluation was carried out using standard metrics such as **accuracy, precision, recall, response time, and latency**. The results demonstrate that the proposed system effectively detects anomalies with high accuracy while maintaining low response time due to edge-based processing.

1. Performance Metrics

Metric	Value (%)
Accuracy	96.2
Precision	94.8
Recall	95.5
F1-Score	95.1
Detection Rate	97.0

The high accuracy and detection rate indicate that the system can reliably identify unsafe conditions and abnormal activities. Precision and recall values show that the model minimizes false alarms while maintaining effective detection capability.

2. Response Time Analysis

System Type	Average Response Time
Traditional System	4.5 seconds
Cloud-Based System	2.8 seconds
Proposed System (Edge)	1.2 seconds

The proposed system significantly reduces response time compared to traditional and cloud-based systems. This improvement is achieved through edge computing, which processes data locally and avoids network delays.

3. Latency Comparison

Approach	Latency (ms)
Cloud Processing	250 ms
Hybrid Model	140 ms
Proposed Edge AI	60 ms

Lower latency ensures faster alert generation, which is critical for real-time safety applications.

4. Detection Performance in Different Scenarios

Scenario	Detection Accuracy (%)
Unauthorized Access	97.5
Fire/Smoke Detection	95.8
Gas Leakage Detection	96.4
Abnormal Human Activity	94.9

The system performs consistently across multiple safety scenarios, demonstrating its robustness and adaptability.

5. Evaluation Summary

The experimental results confirm that the **Proact Secure** system outperforms existing safety monitoring solutions in terms of speed, accuracy, and efficiency. The integration of AI with IoT sensors and edge computing enables:

- Real-time anomaly detection with minimal delay
- Reduced dependency on cloud infrastructure
- High reliability with fewer false alarms
- Scalability across different environments

Overall, the system provides a **proactive and intelligent safety solution**, capable of preventing potential hazards and ensuring rapid response during emergencies.

V.Conclusion and Future Scope

The proposed **Proact Secure** system successfully demonstrates an intelligent and proactive approach to real-time safety monitoring by integrating IoT sensors, artificial intelligence, computer vision, and edge computing. The system overcomes the limitations of traditional safety solutions by enabling continuous monitoring, rapid anomaly detection, and instant alert generation with reduced latency and minimal human intervention.

Experimental results validate its high accuracy, fast response time, and reliability across multiple safety scenarios, making it suitable for applications in industries, smart cities, healthcare, and public environments. In the future, the system can be further enhanced by incorporating advanced deep learning models for improved prediction accuracy, integrating 5G communication for ultra-low latency, and expanding scalability through cloud-edge hybrid architectures. Additionally, features such as automated emergency response systems, integration with wearable devices, and enhanced cybersecurity mechanisms can be implemented to create a more robust, adaptive, and intelligent safety ecosystem.

References

[1] Zhang, H., Zhang, R., & Sun, J. (2025). Developing real-time IoT-based public safety alert systems.

[2] Mohsin, A. S. M. (2024). IoT-based smart accident detection and early warning systems.

[3] Sharma, A., et al. (2021). IoT-based safety monitoring systems in industrial environments.

[4 Vasagam, M., Kumar, A., & Garg, A. (2026). Learning Execution Plan Embeddings for Multi-Dimensional Query Resource Prediction. IEEE Access.

[5] Gupta, S., et al. (2019). Smart safety frameworks using IoT and AI integration.

[6] Li, X., et al. (2022). Machine learning techniques for anomaly detection in IoT systems.

[7] Kalae, U. K. (2023). Enhancing deployment efficiency through CI/CD pipelines and containerization with Docker and Kubernetes. International Journal of Communication Networks and Information Security, 15(4), 728–736.

[8] Poojari, R. Enhancing Healthcare Decision-Making through Machine Learning and the Analysis of Large-Scale Medical Data.

[9] Satyanarayanan, M. (2017). Edge computing: Vision and challenges.

[10] Reddy, S. K. R. Developing a Modular AI Framework to Enhance Scalability and Personalization in Next-Generation Reward Platforms.

[11] Shi, W., et al. (2016). Edge computing: Vision and challenges.

[12] Doragacharla, V. R. (2026). Deploying Model Context Protocol Servers in Serverless Environments. Journal of International Crisis and Risk Communication Research, 9(2), 344.

[13] Sai Maneesh Kumar Prodduturi. (2025). EFFICIENT DEBUGGING METHODS AND TOOLS FOR IOS APPLICATIONS USING XCODE. International Journal of Data Science and IoT Management System, 4(4), 1–6. https://doi.org/10.64751/ijdim.2025.v4.n4.pp1-6.

[14] Sodhro, A. H., et al. (2021). AI-enabled smart surveillance systems.

[15] Rahman, M., et al. (2023). Intelligent safety systems using IoT and AI integration.