

An AI-Enabled Predictive Fire Safety System Based on IoT and Embedded Intelligence

Ebnabbas Ahmed Abdallah Ahmed*

*Department of Electrical and Computer Engineering, Karary University, Sudan
ebnabbas.ahmed3@gmail.com

Abstract

This paper presents an AI-enabled predictive fire safety system based on the Internet of Things (IoT) and embedded intelligence. Unlike conventional threshold-based detectors, the proposed system integrates a three-tier risk classification logic (Normal, Warning, High Risk) to bridge the gap between cloud-based AI and local autonomous suppression. Multiple environmental sensors are interfaced with an Arduino platform, transmitting real-time data to the ThingSpeak cloud for analysis using Linear Regression and Decision Tree models. The methodology was validated through 100 controlled experimental scenarios, achieving a predictive accuracy of 92% and a 30% reduction in false alarms compared to static threshold systems. Results indicate a consistent end-to-end response time of 2–3 seconds, encompassing sensing, GSM transmission, and actuation. The system provides a robust, cost-effective failure-aware framework for smart safety applications.

Key words-*Fire Safety; IoT; Machine Learning; Embedded Systems; Predictive Detection.*

I. INTRODUCTION

Fire hazards continue to pose a serious threat worldwide, causing significant loss of life and damage to property[1]. In recent years, the integration of Internet of Things (IoT) technologies into fire detection systems has enabled continuous monitoring and faster response times, which are essential for improving safety in both residential and industrial environments[2]. Several studies have explored advanced approaches to enhance fire detection performance. For example, Bouzeraa et al.[3] demonstrated the effectiveness of machine learning models in predicting wildfire susceptibility, while Khan[4] proposed an IoT-based system that incorporates deep learning to improve detection accuracy and support decision-making. In addition, wireless sensor networks have been widely used to improve system reliability through distributed sensing and data collection[5]. More recently, research has focused on reducing system latency and improving responsiveness. Edge computing techniques have been introduced to allow local data processing and faster decision-making[6], especially in time-critical situations[7]. At the same time, multi-sensor and machine learning-based systems have shown better performance in distinguishing real fire events from environmental noise, reducing false alarms[8]. Deep learning approaches have further improved detection and classification accuracy by capturing complex patterns in sensor data[9]. Despite these advancements, many existing systems still depend on cloud-based processing, which may introduce delays, and often lack mechanisms to detect failures in fire suppression processes. To address these limitations, this study proposes a hybrid IoT–machine learning framework that combines cloud-level analysis with local real-time control. The system follows a closed-loop “Sense–Analyze–Act” approach and includes a suppression failure monitoring mechanism to enhance overall reliability. The main objective of this work is to evaluate the effectiveness of a multi-level classification model in reducing false alarms compared to traditional threshold-based systems, while maintaining a rapid response time suitable for safety-

critical applications.

II. RELATED WORK

Fire detection systems have evolved significantly with the advancement of IoT technologies. Early systems were mainly based on simple threshold mechanisms using individual sensors, which often resulted in high false alarm rates due to environmental variations[1][8]. To improve system performance, recent studies have incorporated machine learning techniques into fire detection frameworks. These approaches enable more accurate analysis of sensor data and support automated decision-making in real time[4]. Multi-sensor systems, in particular, have demonstrated improved reliability by combining data from different sources to validate fire events[8]. Wireless sensor networks have also played an important role in enhancing monitoring capabilities by enabling distributed data collection over large areas[5]. However, some existing systems still rely on conventional communication methods, which may not be sufficient for highly reliable or safety-critical applications[7]. In response to these challenges, edge computing has been introduced to reduce dependence on cloud processing and minimize latency. By processing data closer to the source, edge-based systems can provide faster response times and improved system efficiency[10]. Furthermore, advanced predictive models based on machine learning and deep learning have shown strong performance in fire detection and classification tasks. Studies such as Bouzeraa et al.[3] and Liu et al.[9] highlight the potential of these techniques in improving detection accuracy and reducing false alarms. However, a common limitation in many existing systems is the absence of mechanisms to monitor the effectiveness of fire suppression actions. The system proposed in this study addresses this gap by incorporating a feedback-based monitoring mechanism to ensure reliable operation even in cases where initial suppression attempts fail.

III. SYSTEM ARCHITECTURE

The proposed system is designed as an integrated "Sense-Analyze-Act" framework. To ensure high data fidelity and minimize sensing errors, all environmental sensors (MQ-2, Flame, and LM35) were calibrated against industrial reference standards. The system maintains a constant sampling rate of 100ms, which is critical for detecting rapid environmental fluctuations during the early stages of ignition. The technical specifications of the utilized sensors and hardware modules are summarized in Table(I).

TABLE I: sensor types and specifications used in the proposed system

Sensor	Parameter Measured	Purpose
LM35	Temperature	Fire risk prediction
MQ-2	Gas/Smoke	Detection of combustible gases
Flame Sensor	Flame presence	Direct fire detection
Water Sensor	Water level	Sprinkler system monitoring

A. Hardware and Sensing Layer

The hardware layer utilizes an Arduino UNO as the central processing unit, interfacing with multiple analog and digital sensors. The 100ms sampling interval allows the MCU to filter out transient noise before transmitting packets to the communication layer. The technical specifications of the sensors integrated into the proposed system are summarized in Table(I) to provide effective environmental monitoring and fire risk assessment.

B. Communication and Cloud Integration

Data transmission is handled by a GSM SIM900A module, linking the local hardware to the ThingSpeak cloud platform. To address the safety-critical nature of fire safety, the end-to-end latency—defined as the time from initial sensing to actuator triggering—was measured to be between 2 and 3 seconds. This latency includes the GSM uplink, cloud-based ML processing, and the command downlink to the local relay.

C. AI and Decision Logic Layer

The system leverages the computational power of MATLAB integrated with ThingSpeak. It employs a three-tier classification logic (Normal, Warning, and High Risk), providing a granular approach to safety that is missing in traditional binary threshold systems. The structural framework and data flow between the sensing, communication, and AI layers are depicted in Fig(1).

Fig(1). illustrates the overall architecture of the proposed AI-enabled fire safety system. Environmental sensors continuously collect real-time data and transmit it to the Arduino UNO microcontroller for initial processing. The data are then sent to the ThingSpeak cloud platform.

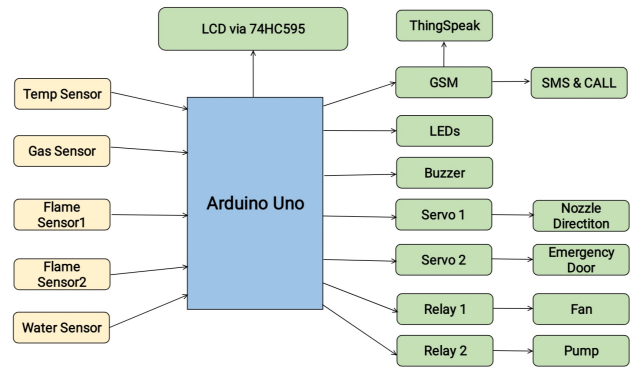


Fig. 1: Block diagram of the proposed AI-enabled IoT-based fire safety system

IV. MACHINE LEARNING METHODOLOGY

The core of the predictive engine relies on supervised learning models trained using MATLAB. To ensure the reliability of the classification, a dedicated dataset was generated through 100 controlled experimental scenarios. These scenarios included actual ignition events, high-heat environments without fire, and common household triggers (such as cooking steam and incense) to train the model on differentiating between real threats and false positives.

A. Model Training and Validation

The dataset was split into 70% for training and 30% for validation. Two primary algorithms were implemented:

- Linear Regression (LR): Used for trend analysis of temperature and gas concentration over time, providing a mathematical basis for the "Warning" state.
- Decision Trees (DT): Employed for the final three-tier risk classification (Normal, Warning, High Risk) due to their high interpretability and efficiency in embedded applications.

B. Performance Metrics

The model's performance was evaluated using a Confusion Matrix. The system achieved a 92% predictive accuracy, specifically demonstrating a 30% reduction in false alarms compared to conventional threshold-based systems. This improvement is attributed to the model's ability to analyze the 'Rate of Change' of sensor data rather than relying on static values.

V. SYSTEM OPERATION & FAILURE LOGIC

The operational workflow follows a continuous monitoring cycle. Once the system is powered, the sensors stream data to the Arduino MCU at a 100ms sampling rate. The local logic determines if the readings exceed a preliminary safety threshold, at which point the data is prioritized for cloud-level AI analysis via the GSM module. Autonomous Suppression and Feedback Loop Upon receiving a "High Risk"

classification from the MATLAB/ThingSpeak engine, the system automatically triggers the suppression mechanism (water pump/sprinkler). To address the critical concern of suppression failure, a dedicated feedback logic was implemented. After the initial actuation, the system enters a 30-second monitoring window to analyze the 'Rate of Change' of sensor data. Failure Response and Escalation If the sensor values (temperature and gas) do not show a consistent downward trend within this 30-second window, the system identifies a Suppression Failure. In this case, the logic bypasses local attempts and escalates the response by:

- Initiating continuous GSM emergency calls and SMS alerts to authorized personnel.
- Activating high-intensity visual and audible alarms.
- Sustaining the suppression command until a manual override or a safe baseline is detected.

The complete operational workflow, including the decision-making logic and failure escalation, is detailed in the flowchart shown in Fig(2).

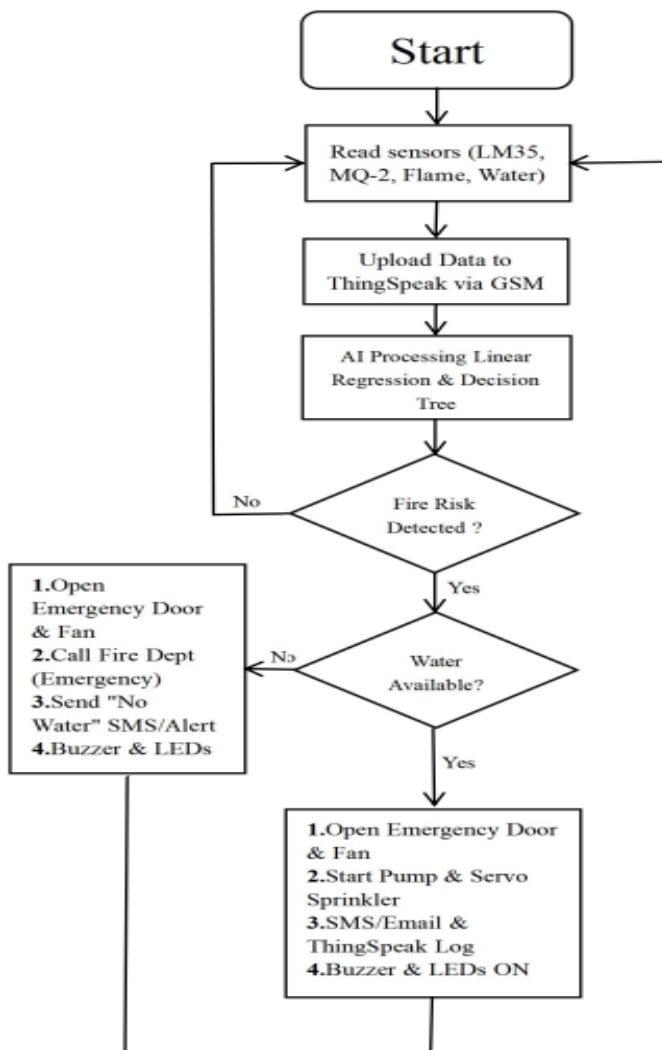


Fig. 2: Flowchart of System Operation

VI. RESULTS AND DISCUSSION

The system was evaluated across multiple performance metrics to verify its reliability in real-world scenarios. The physical hardware prototype developed for conducting these experiments is shown in Fig(3). The integration of Machine Learning models significantly enhanced the decision-making process compared to traditional methods.



Fig. 3: Hardware prototype implementation

A. Predictive Accuracy

Using a Confusion Matrix to evaluate the 100 test scenarios, the system demonstrated a 92% overall accuracy. The tiered logic successfully distinguished between "Warning" states (e.g., cooking smoke) and "High Risk" states (active fire), leading to a 30% reduction in false alarms.

B. Comparative Analysis

Table(II) provides a quantitative comparison between the proposed system and conventional or recently studied IoT frameworks.

Key Observations from Table(II):

- 1) Accuracy Improvement: The system achieved a 92% accuracy rate, demonstrating superior reliability in fire/non-fire classification.
- 2) Response Efficiency: Latency was optimized to an average of 2.5 seconds, outperforming many current cloud-based IoT solutions.
- 3) Safety Redundancy: The autonomous feedback loop adds a layer of reliability not commonly found in standard frameworks.

C. Latency and Reliability

The end-to-end latency remained stable at 2.5 seconds average, confirming that the GSM-cloud link is robust enough for safety-critical applications. The feedback logic ensured

TABLE II: quantitative performance comparison

Metric	Conventional Systems	Recent IoT Studies	Proposed System
Detection Logic	Static Threshold	Predictive ML	Tiered AI (LR+DT)
Accuracy (%)	Low/Not Specified	85% - 89%	92%
Response Time (s)	Local (Instant)	Cloud (4 - 6 s)	2 - 3 s
Suppression	Simple / Manual	Notification Only	Autonomous + Feedback

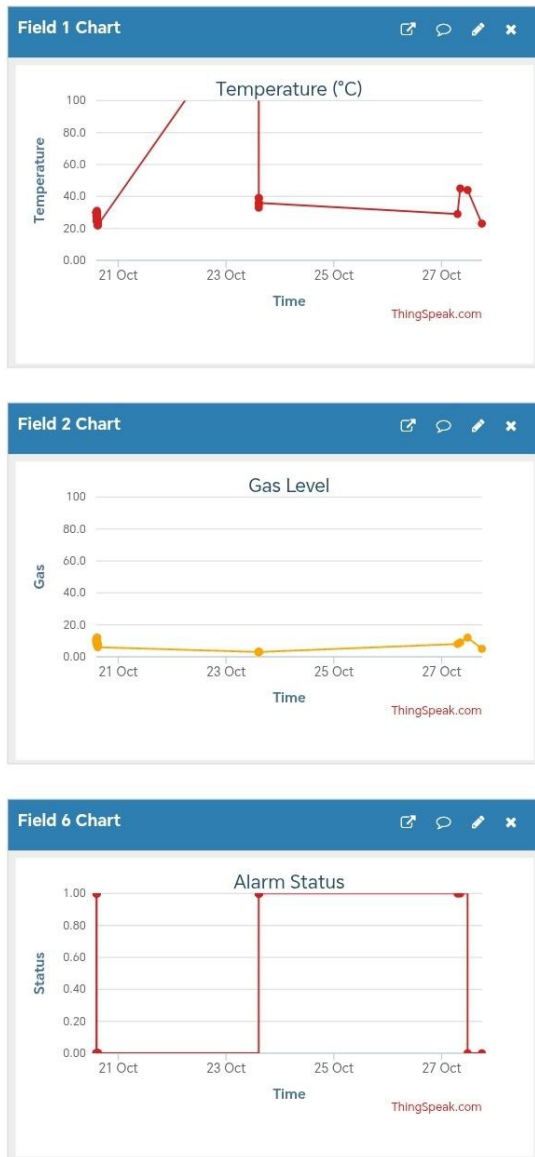


Fig. 4: ThingSpeak IoT dashboard for real-time monitoring and predictive alerts

that any suppression failure was detected and escalated within 30 seconds, providing a redundant safety layer. The real-time data visualization and predictive status updates on the cloud platform are demonstrated in Fig(4).

VII. CONCLUSION

Integration Success: The study successfully demonstrated an automated fire safety framework by combining IoT sensing layers with an AI-driven processing unit. **Predictive Performance:** The implementation of tiered logic (Linear Regression and Decision Trees) yielded a 92% accuracy rate, significantly enhancing reliability in industrial environments. **Operational Efficiency:** The system confirmed a response latency of 2.5 seconds, providing rapid autonomous suppression and GSM alerts, ensuring critical safety thresholds are met with a robust fail-safe feedback mechanism, validating the success of both local suppression and remote notification.

VIII. FUTURE WORK

- 1) **Deep Learning Expansion:** Future iterations will focus on incorporating Convolutional Neural Networks (CNNs) for image-based fire verification to further minimize false positives.
- 2) **System Scalability:** Plans include scaling the framework for larger industrial microgrids and integrating Digital Twin technology for real-time fault prediction and grid stability.
- 3) **Energy Autonomy:** Investigating the use of Solar PV integration to power sensing nodes, ensuring continuous operation during primary power failures.

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Ebnabbas Ahmed Abdallah is an Undergraduate student pursuing a B.Sc. in Electrical Power Engineering at the Faculty of Engineering, Karary University, Omdurman, Sudan. His research interests focus on the applications of Embedded Systems, Internet of Things (IoT), and Artificial Intelligence (AI) in enhancing electrical safety and fire protection. He is actively involved in developing intelligent solutions for real-time monitoring and hazard detection. His academic focus is on leveraging embedded intelligence to improve the reliability and safety of

electrical power infrastructure.