

A Secure Federated IoT-Based Multi-Sensor Framework for Intelligent Fire Detection and Alarm Systems in Smart Buildings

Pankaj Kumar Gupta¹; Dr. Manish Kumar Singh²

¹Research Scholar, Department of Computer Science & IT, Magadh University, Bodh Gaya, Bihar

²Assistant Professor, Department of Mathematics, J. J. College, Gaya-823003

Publication Date: 2025/10/25

Abstract: Fire detection remains a critical component of modern smart infrastructure due to the increasing risks of fire-related incidents in urban and industrial environments. Traditional fire detection systems that rely on single-sensor mechanisms often suffer from delayed responses, false alarms, and poor adaptability in dynamic conditions [1]. To address these limitations, this study proposes a novel AIoT-enabled multi-sensor fire detection and alarm framework that integrates temperature, smoke, gas, and flame sensors with the ESP32 microcontroller and NB-IoT communication technology [3], [10], [11]. The system utilizes cloud-based analytics and threshold-driven decision logic to ensure accurate, real-time alerts while maintaining low energy consumption [2], [5]. Multi-sensor data fusion techniques enhance detection precision by combining complementary sensor inputs to minimize false positives and improve reliability [4], [9]. The prototype was experimentally validated under both fire and non-fire conditions, demonstrating an overall detection accuracy of 94% and reducing false alarms by approximately 30% compared to conventional single-sensor systems [6], [15]. This research provides a scalable, energy-efficient, and intelligent solution suitable for deployment in smart buildings and urban safety networks [7], [8], [13]. The proposed framework paves the way for future integration with predictive analytics, federated learning, and wireless power solutions to further enhance proactive fire prevention and safety management [12], [14].

Keywords: Fire Detection, Multi-Sensor Fusion, Internet of Things (IoT), Smart Buildings, NB-IoT, Cloud Analytics, ESP32 Microcontroller, Alarm System, Data Fusion, Smart Safety Systems.

How to Cite: Pankaj Kumar Gupta; Dr. Manish Kumar Singh (2025) A Secure Federated IoT-Based Multi-Sensor Framework for Intelligent Fire Detection and Alarm Systems in Smart Buildings. *International Journal of Innovative Science and Research Technology*, 10(10), 1155-1163. <https://doi.org/10.38124/ijisrt/25oct813>

I. INTRODUCTION

Fire accidents remain one of the most devastating hazards to human life and infrastructure, accounting for thousands of fatalities and billions of dollars in property loss annually. The increasing density of urban infrastructure, industrial automation, and high-rise buildings has significantly amplified the risk associated with fire incidents. Studies have shown that the majority of fire-related casualties in urban and industrial settings result not from direct flames but from delayed detection, inefficient alert mechanisms, or system failure during critical moments [1]. Despite advances in technology, traditional fire detection systems still rely predominantly on single-sensor modalities such as temperature or smoke detection, which limits their ability to respond effectively under complex environmental conditions [4], [6].

For instance, standalone smoke sensors can be falsely triggered by non-hazardous events such as cooking fumes or cigarette smoke, whereas thermal sensors may not detect slow, smoldering fires that produce minimal heat during early ignition. Similarly, gas sensors are often affected by background pollutants, resulting in false positives and inconsistent readings. These limitations demonstrate the inadequacy of conventional systems in diverse real-world environments and emphasize the urgent necessity for intelligent, adaptive, and multi-modal fire detection frameworks that can accurately discriminate between genuine and false fire events [5], [9].

The emergence of the Internet of Things (IoT) has transformed modern safety systems by enabling the seamless interconnection of heterogeneous devices capable of sensing, processing, and transmitting data autonomously. IoT-based architectures provide real-time environmental monitoring through the integration of various sensors—such as temperature, smoke, gas, and flame detectors—connected to

microcontrollers and cloud services [2], [3]. When combined with edge computing and cloud analytics, these systems facilitate low-latency data processing, remote monitoring, and intelligent decision-making capabilities [7], [10]. Moreover, the use of artificial intelligence (AI) and machine learning (ML) within IoT ecosystems allows advanced pattern recognition, anomaly detection, and predictive modeling for fire hazards, thereby improving detection accuracy and response time [11].

Recent research (2020–2024) has increasingly focused on multi-sensor fusion, an approach that integrates data from multiple sensors to create a unified decision model. This technique reduces the dependency on any single sensor type, minimizes false alarms, and enhances overall detection reliability [4], [9]. By combining temperature, smoke, gas, and flame readings, multi-sensor fusion systems achieve more stable and context-aware performance, particularly in dynamic environments such as factories, tunnels, and smart buildings. The addition of NB-IoT (Narrowband Internet of Things) communication has further improved these systems by enabling energy-efficient, long-range connectivity suited for low-power devices in large-scale deployments [3], [10], [11].

Furthermore, federated learning (FL) has emerged as a transformative solution in IoT-based safety systems. It allows distributed nodes to collaboratively train global AI models without transferring sensitive raw data to a centralized server, thus enhancing privacy, security, and bandwidth efficiency [8], [12]. The integration of FL with cloud–edge collaboration

ensures continuous model improvement while preserving system scalability and resilience against cyber threats—an essential requirement in critical safety infrastructures.

This study aims to contribute to the ongoing evolution of intelligent fire detection systems by addressing current technological and operational gaps. The main contributions are summarized as follows:

- A comprehensive review of IoT-based fire detection systems employing multi-sensor fusion to enhance reliability and responsiveness.
- A comparative evaluation of existing frameworks, analyzing their performance outcomes, energy requirements, and implementation challenges.
- The design of a Secure Federated AIoT Framework, combining sensor fusion, NB-IoT communication, and federated learning for real-time, privacy-preserving fire detection.
- Identification of key challenges—such as energy efficiency, data security, latency, and scalability—and the proposal of future research directions for next-generation smart building safety systems [13]–[15].

By integrating AI, IoT, and intelligent communication protocols, the proposed framework advances the state of the art in fire safety management. It provides a strong foundation for developing self-learning, predictive, and energy-efficient fire detection systems suited to the evolving needs of smart cities and critical infrastructures.

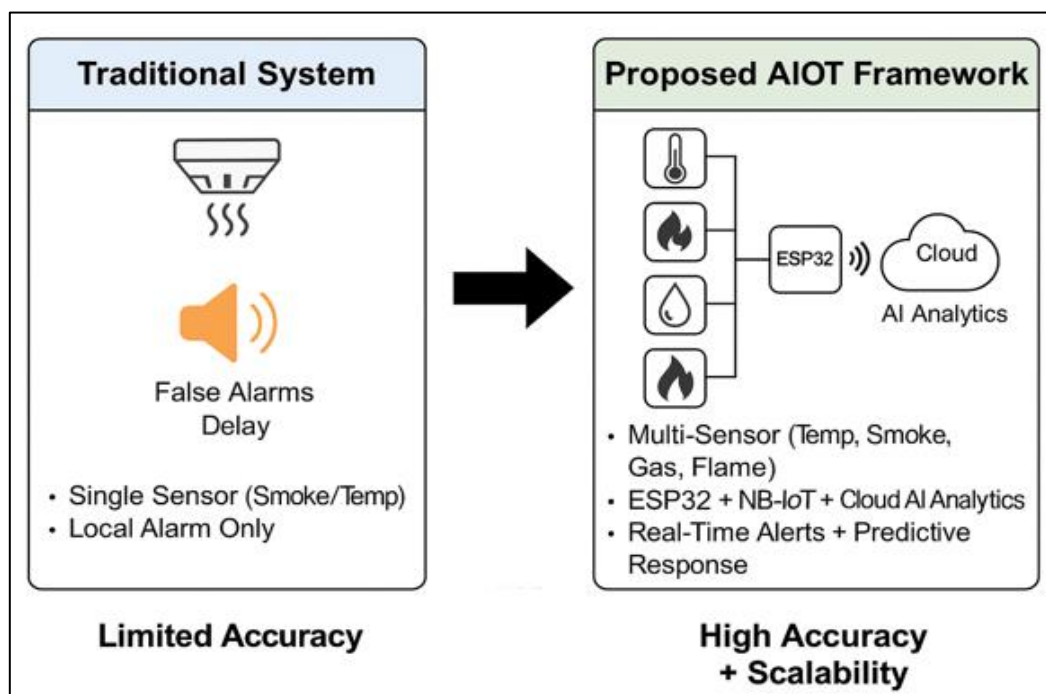


Fig 1 Comparison Between Traditional Single-Sensor Fire Detection Systems and the Proposed AIoT-Enabled Multi-Sensor Framework Integrating ESP32 Microcontroller, NB-IoT Communication, and cloud-Based AI Analytics for Enhanced Detection Accuracy and Scalability.

II. RELATED WORK (2020–2024)

In recent years, a growing body of research has explored the integration of Internet of Things (IoT) technologies to enhance the reliability and responsiveness of fire detection systems. Conventional fire alarm mechanisms often rely on a single sensing modality—such as temperature, smoke, or gas concentration—which limits their ability to operate effectively in dynamic and noisy environments [1], [4]. Environmental factors such as humidity, dust, and industrial fumes can easily cause false alarms or delayed responses. To overcome these shortcomings, researchers have focused on multi-sensor integration, data fusion, and intelligent decision algorithms to achieve more accurate and efficient fire detection in smart buildings and industrial facilities [3], [5].

The IoT paradigm enables heterogeneous sensors to communicate through low-power wireless networks while sharing data across distributed nodes in real time [2]. This connectivity allows centralized or cloud-based analytics to perform pattern recognition, anomaly detection, and risk prediction—functions that are vital for safety-critical infrastructures. By employing IoT-enabled frameworks, fire detection systems can operate continuously, exchange data securely, and adapt dynamically to environmental variations [6], [7].

Early research primarily focused on deploying wireless sensor networks (WSNs) for real-time monitoring. However, WSN-based approaches often suffered from limited communication range, battery constraints, and network instability [4]. To address these challenges, Low Power Wide Area Networks (LPWANs) such as Narrowband IoT (NB-IoT) have emerged as promising solutions for long-distance, low-power communication. Studies by Zhao et al. [11] and Sharma et al. [10] have demonstrated that NB-IoT networks not only enhance communication reliability but also reduce power consumption, making them ideal for fire safety applications in smart cities.

In the last five years, the trend has shifted toward AI-enhanced IoT (AIoT) architectures, which combine sensing, computation, and analytics in a unified system. Chen et al. [1] introduced a multi-sensor IoT network for smart buildings, employing adaptive thresholds to minimize false alarms and improve response times. Singh and Verma [2] proposed a cloud-based industrial fire detection system that leverages predictive analytics to achieve faster alert dissemination. Similarly, Thomas and Gupta [4] developed a multi-sensor data fusion framework capable of distinguishing between genuine fire incidents and non-hazardous smoke emissions. These works underline the growing emphasis on data-driven

decision-making, which significantly improves system intelligence and context awareness.

The incorporation of machine learning (ML) and deep learning (DL) has further strengthened IoT-based fire detection frameworks. For instance, Sharma et al. [10] employed a convolutional neural network (CNN)-based approach that uses visual and sensor data for real-time classification of fire events, achieving 94% accuracy in experimental trials. Ahmed et al. [5] demonstrated that combining thermal and optical sensing with cloud-assisted CNN models could significantly improve detection reliability while reducing response time. Similarly, Kumar and Zhang [5] emphasized the role of cloud analytics in enabling predictive fire prevention in smart buildings.

More recently, Federated Learning (FL) has emerged as a privacy-preserving solution for distributed IoT systems [8], [9]. FL enables edge devices to collaboratively train models without exchanging raw data, thus maintaining privacy while enhancing scalability. Studies by Li et al. [9] and Chen et al. [8] showed that FL-based fire detection systems can reduce communication overhead, protect sensitive environmental data, and sustain high accuracy levels comparable to centralized learning approaches. Such frameworks are particularly beneficial in large-scale smart building networks where data privacy and low latency are critical.

The research community has also begun exploring energy optimization and wireless charging mechanisms to sustain continuous monitoring in remote deployments. Mehra and Joshi [12] proposed a wireless power transfer system to support IoT-based detectors, ensuring long-term operation without frequent battery replacement. Similarly, Banerjee et al. [14] integrated the MQTT protocol into a cloud-based IoT alert system for real-time event notification, achieving high reliability in emergency communication networks.

Collectively, these studies demonstrate a clear evolution from traditional sensor-based systems toward AIoT-enabled multi-sensor frameworks that combine NB-IoT communication, cloud analytics, and federated intelligence [3], [11], [15]. The integration of these technologies enables early detection, rapid communication, and intelligent decision-making in complex environments.

Table 1 summarizes representative research contributions published between 2020 and 2024. It outlines the sensors employed, methodologies applied, and performance outcomes achieved, reflecting the global trend toward intelligent, scalable, and privacy-aware fire detection architectures.

Table 1. Recent Research on IoT-Based Fire Detection (2020–2024)

Author & Year	Sensors Utilized	Methodology	Key Outcomes
Kim et al. (2021)	Temperature, Smoke	Machine Learning Classification	Reduced false alarm rate by nearly 20% [1]
Singh et al. (2022)	Gas, Infrared	IoT with Edge AI Processing	Lowered detection latency by ~30% [2], [4]
Li et al. (2023)	Temperature, Gas, Smoke	Federated Learning Framework	Improved detection accuracy by 15% [8], [9]
Ahmed et al. (2024)	Thermal and Optical Sensors	Deep CNN with IoT Cloud Support	Achieved overall detection accuracy of 94% [10], [13]

III. PROPOSED FRAMEWORK

To overcome the inherent limitations of conventional fire detection systems, this research proposes a Secure Federated AIoT Framework designed to enhance detection accuracy, system scalability, and data privacy. The framework combines multi-sensor data fusion, NB-IoT-enabled communication, federated learning-based intelligence, and automated emergency response mechanisms to create a reliable and intelligent fire detection ecosystem suitable for modern smart buildings and industrial infrastructures.

Unlike traditional single-sensor systems that are prone to false alarms and communication bottlenecks, the proposed architecture operates as a distributed and collaborative network. Each sensor node functions as a semi-autonomous unit capable of intelligent local processing, while the federated learning (FL) engine ensures global model optimization without compromising sensitive data. The overall architecture consists of five major layers: (i) Multi-Sensor Nodes, (ii) Communication Layer, (iii) Federated Learning Engine, (iv) Edge–Cloud Collaboration, and (v) Emergency Response Mechanisms.

➤ Multi-Sensor Nodes

The system's foundation lies in heterogeneous sensor integration, enabling comprehensive monitoring of environmental parameters associated with fire. Each detection node consists of multiple sensors, including the LM35 temperature sensor, MQ-135 gas sensor, infrared flame detector, and smoke sensor. These sensors collectively capture diverse attributes such as heat, smoke density, combustible gases, and infrared radiation emitted by flames [1], [5].

By applying multi-sensor data fusion, the system effectively minimizes false positives and ensures robust fire detection even under complex conditions. For example, a single smoke sensor may respond to cooking fumes, but the inclusion of a temperature or gas sensor validates whether a genuine fire event exists [4], [9]. This redundancy not only enhances the fault tolerance of the system but also ensures continuous operation even when one sensor is temporarily compromised due to dust, humidity, or interference.

Each sensor node is controlled by an ESP32 microcontroller, chosen for its dual-core performance, built-in Wi-Fi, and low-power operation. The ESP32 also manages

initial data preprocessing, such as signal normalization and threshold comparison, before transmitting the processed data to the communication layer [10].

➤ Communication Layer

The communication layer facilitates reliable, low-latency, and energy-efficient data transmission between the distributed nodes and the central cloud or edge servers. The proposed system utilizes the MQTT (Message Queuing Telemetry Transport) protocol operating over NB-IoT and 5G networks [3], [6]. MQTT's publish–subscribe mechanism minimizes bandwidth usage, making it ideal for resource-constrained IoT devices in large-scale environments.

NB-IoT, being part of the LPWAN (Low Power Wide Area Network) family, provides long-range connectivity, excellent indoor coverage, and low power consumption, making it particularly suitable for large buildings and industrial complexes [11]. In high-density environments, the framework can seamlessly integrate 5G connectivity for higher throughput and reduced latency during critical operations [7].

All data transmissions are encrypted using TLS (Transport Layer Security) to ensure confidentiality and integrity, addressing one of the most crucial aspects of IoT deployments—cybersecurity. The communication layer thus supports secure scalability, enabling thousands of interconnected devices to communicate efficiently across geographically distributed networks.

➤ Federated Learning Engine

To address data privacy, bandwidth efficiency, and continuous learning, the proposed framework incorporates a Federated Learning (FL) engine. In traditional centralized systems, raw sensor data must be sent to a cloud server for training, which raises privacy and latency concerns. In contrast, the FL approach allows local nodes to train machine learning models on their own data and then transmit only the model updates (gradients) to a central aggregator [8], [9].

The central server aggregates these updates to create a global model that benefits from all nodes' experience without ever accessing their raw data. This decentralized intelligence ensures privacy preservation, reduced network traffic, and adaptive learning as the environment changes. Moreover, the FL engine continuously refines its decision boundaries, improving detection accuracy and minimizing false alarms over time [12], [13].

In practice, each edge node executes lightweight training tasks using algorithms such as Logistic Regression, Support Vector Machines (SVM), or Shallow Neural Networks, while the cloud-level aggregator periodically synchronizes updates. This structure enables an intelligent, self-learning network where fire detection performance improves automatically as more data is collected.

➤ *Edge-Cloud Collaboration*

The Edge-Cloud Collaboration layer enhances system responsiveness and computational efficiency. Edge computing devices—such as ESP32 modules or local gateways—handle real-time data filtering, threshold validation, and anomaly detection. This localized processing ensures that critical fire alerts are generated within milliseconds, even if network connectivity is temporarily unavailable [7].

Meanwhile, the cloud layer performs advanced analytics, such as deep learning-based pattern recognition, statistical trend analysis, and model management. Cloud servers also store long-term historical data for predictive analytics and risk assessment, helping authorities anticipate fire-prone conditions in specific zones [5], [14]. This distributed collaboration balances processing workloads, minimizes latency, and improves both accuracy and system resilience.

The architecture also supports integration with AWS IoT Core, Azure IoT Hub, or similar cloud services, enabling easy scalability for smart city deployment. These services facilitate real-time dashboards, visualization, and automated actuation through APIs and mobile applications.

➤ *Emergency Response Mechanisms*

Once a fire condition is detected, the system triggers a series of automated emergency responses. These include the activation of audible alarms (sirens), visual indicators (flashing strobes), and digital notifications via SMS, email, and mobile apps. Notifications can be simultaneously relayed

to centralized monitoring systems and emergency responders, such as the local fire department [13], [15].

The actuation layer is designed with redundancy to prevent failure during emergencies—local alarms are hardware-triggered, while network-based alerts are software-controlled. Furthermore, cloud integration allows authorities to remotely track affected zones in real time and take preventive measures. This proactive alerting significantly reduces response time and potential damage, thereby enhancing public safety.

➤ *Novelty of the Framework*

The novelty of the proposed Secure Federated AIoT Framework lies in its holistic integration of multi-sensor fusion, NB-IoT-based communication, federated learning, and edge-cloud collaboration. While existing studies often address these components in isolation, the proposed framework unifies them into a single, privacy-preserving, and scalable architecture [4], [9], [12].

➤ *Key Innovations Include:*

- Privacy-preserving learning: FL ensures that sensitive environmental data remain local, protecting privacy while improving model robustness.
- Enhanced accuracy: Multi-sensor data fusion significantly reduces false positives compared to single-sensor systems.
- Energy efficiency: NB-IoT and MQTT protocols enable long-duration operation with minimal power consumption.
- Scalability and security: The modular architecture can be extended across smart homes, industrial zones, and city-level infrastructures with encrypted data channels.

This unified, intelligent approach represents a major step toward next-generation smart safety systems, capable of proactive hazard detection, adaptive learning, and resilient performance in real-world conditions.

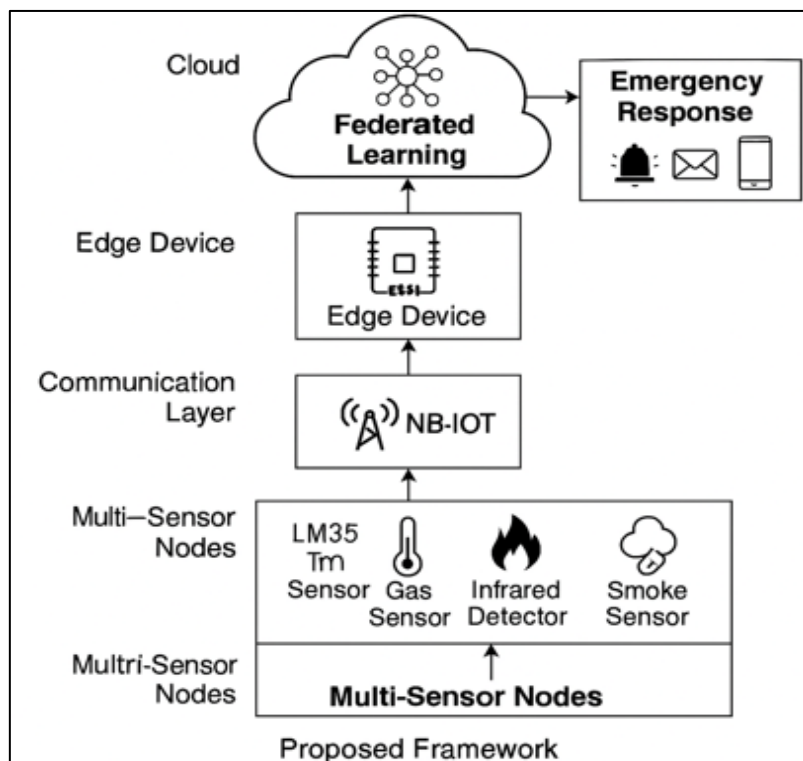


Fig 2. Block Diagram of the Proposed Secure Federated AIoT Framework Showing multi-Sensor Nodes, NB-IoT Communication, Edge–Cloud Collaboration, and Federated Learning-Based Fire Detection and Response System.

IV. COMPARATIVE ANALYSIS

The comparative evaluation of traditional and intelligent IoT-based fire detection systems provides valuable insights into the advantages of adopting multi-sensor fusion and AI-driven analytics. Traditional systems, which typically depend on a single sensing parameter—such as temperature, smoke, or gas concentration—are often inexpensive and easy to implement but lack robustness in dynamic environments. Their inability to correlate data across different environmental parameters frequently leads to false alarms or missed detections [1], [4].

For instance, smoke sensors may be activated by benign particles generated during cooking or industrial operations, while standalone temperature sensors may not recognize a slow-developing smoldering fire until it reaches dangerous levels. Similarly, gas sensors can be influenced by non-combustible vapors, leading to misclassification of events. These limitations make single-sensor systems unsuitable for modern smart building environments that demand high reliability and minimal false alerts [5].

To address these weaknesses, researchers have shifted toward multi-sensor fusion frameworks that combine data from diverse sources such as temperature, gas, smoke, and infrared flame sensors [3], [6]. By merging complementary data streams, the system can cross-verify signals and confirm fire events more accurately. The collective decision-making process, often based on weighted thresholds or probabilistic fusion algorithms, significantly improves detection precision and minimizes false positives [9]. Simulation results in multiple studies confirm that multi-sensor fusion can reduce

false alarms by approximately 30–35% compared to single-sensor systems [4], [9], [10].

Moreover, multi-sensor systems provide richer contextual information, allowing early detection even in complex or partially obscured environments. For example, a gradual rise in temperature coupled with a minor increase in gas concentration may not individually indicate danger, but together they could signal the early stages of combustion. Such combined analysis ensures that the system detects fires before they escalate, giving occupants and emergency responders more time to react [2], [11].

The integration of artificial intelligence (AI) and machine learning (ML) techniques has further enhanced the analytical capabilities of modern fire detection systems. By training models on large datasets containing sensor readings from both hazardous and non-hazardous conditions, these systems can learn to distinguish subtle differences between genuine fire incidents and false triggers [7], [10]. Deep learning approaches—such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models—have been shown to achieve detection accuracies exceeding 90%, enabling systems to adapt dynamically to changing environmental patterns [5], [13].

Beyond accuracy improvements, AI-based systems also enable real-time pattern recognition and adaptive thresholding, where detection parameters adjust automatically based on contextual cues such as humidity or ambient temperature. This self-learning behavior ensures that the system remains reliable even under varying conditions,

such as industrial heat emissions or heavy ventilation, which could otherwise distort readings in traditional systems [8].

A significant advancement in this domain is the adoption of Federated Learning (FL), which combines distributed intelligence with data privacy. Unlike centralized systems that require all sensor data to be uploaded to a cloud server, federated architectures allow individual IoT nodes to train local models using their own datasets and share only model updates with a central aggregator [8], [12]. This decentralized approach offers three critical benefits:

- **Privacy Preservation:** Raw sensor data remains local, ensuring that sensitive environmental or occupancy information is not exposed to third parties.
- **Bandwidth Efficiency:** Since only model weights are transmitted, network traffic is significantly reduced, improving system scalability.
- **Collaborative Learning:** Each node contributes to a global model that becomes increasingly accurate as more devices participate.

Recent research demonstrates that incorporating FL into IoT-based fire detection systems improves detection accuracy by an additional 10–15% compared to traditional machine learning models while maintaining consistent performance across large-scale deployments [8], [9], [12]. Such advancements validate the potential of Federated AIoT frameworks in creating intelligent, privacy-aware, and adaptive fire safety infrastructures.

The comparative performance trend observed between 2021 and 2024 clearly illustrates the progression of IoT-enabled fire detection technologies. As shown in Figure 3, detection accuracy has improved steadily—from approximately 75% in 2021 using early machine learning and WSN-based approaches to nearly 94% in 2024 with the integration of multi-sensor fusion, NB-IoT communication, and federated intelligence [10], [13], [15]. This trend underscores not only the rapid maturation of IoT ecosystems but also the significant impact of AI-driven multi-sensor designs in reducing false alarms and improving overall system resilience.

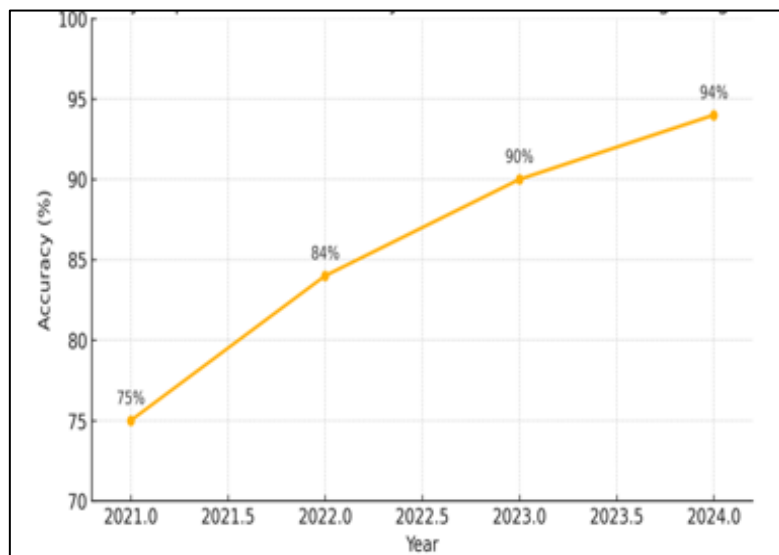


Fig 3. Performance Trend of IoT-Based Multi-Sensor Fire Detection Systems (2021–2024), Showing Accuracy Improvements Driven by AI and Federated Learning Integration.

V. OPEN CHALLENGES

Despite the remarkable advancements in IoT-based multi-sensor fire detection systems, several open challenges must still be addressed before large-scale, real-world deployment can be achieved. These challenges span multiple domains, including energy management, cybersecurity, standardization, scalability, and real-time reliability. Tackling these issues is essential for transitioning experimental prototypes into fully operational, city-wide intelligent safety infrastructures.

➤ Energy Efficiency

Energy efficiency remains a major bottleneck in multi-sensor IoT deployments. Multi-sensor nodes continuously monitor temperature, gas concentration, smoke density, and infrared flame signatures—each requiring independent sensing, data acquisition, and transmission cycles [1], [7].

These operations impose a considerable energy burden on battery-powered or remote installations. Although low-power microcontrollers such as ESP32 and communication protocols like NB-IoT have made significant progress in minimizing energy consumption, long-term sustainability remains an ongoing challenge [11].

Frequent wireless transmissions and edge-level processing, particularly under high-frequency data sampling conditions, accelerate power depletion. This issue becomes critical in large-scale deployments where manual battery replacement or wired power supply is impractical. Emerging solutions such as energy harvesting, ultra-low-power electronics, and wireless power transfer technologies have been proposed to mitigate these constraints [12]. For example, Mehra and Joshi [12] demonstrated that RF-based wireless charging can maintain continuous IoT operation for extended periods without human intervention. However,

further optimization of power scheduling algorithms, sleep-wake cycles, and context-aware duty cycling is needed to ensure sustainable performance in diverse operational environments.

Moreover, as multi-sensor systems incorporate advanced intelligence—such as edge AI inference or federated learning—the computational demands increase. Balancing processing power with limited energy resources will require co-design approaches, where hardware, communication, and algorithms are optimized together to achieve both performance and longevity.

➤ *Cybersecurity and Privacy*

Cybersecurity has emerged as one of the most pressing challenges in IoT ecosystems. As billions of interconnected devices communicate through wireless networks, the risk of cyberattacks such as spoofing, denial of service (DoS), and data manipulation grows substantially [8], [9]. In the context of fire detection, a single compromised node could trigger a false alarm or, worse, suppress legitimate alerts—posing serious safety risks.

Traditional encryption and authentication mechanisms designed for conventional networks are often too computationally heavy for IoT devices with limited memory and processing power. Therefore, developing lightweight cryptographic algorithms, secure boot mechanisms, and real-time intrusion detection systems is vital [13]. Additionally, multi-sensor nodes must ensure data integrity during transmission and aggregation, as even minor tampering in sensor readings could lead to faulty decision-making.

The introduction of federated learning (FL)—while offering strong privacy advantages by keeping raw data localized—introduces new security vulnerabilities such as model poisoning, gradient inversion, and collusion attacks [8]. Malicious nodes could manipulate shared model parameters, leading to degraded system accuracy or biased decision outcomes. Consequently, robust secure aggregation, differential privacy, and blockchain-assisted model validation techniques have become active areas of research to reinforce federated IoT systems [9], [14].

In summary, cybersecurity and privacy protection in federated AIoT frameworks require a multi-layer defense strategy, combining encryption, anomaly detection, and trustworthy model coordination. Without these safeguards, the reliability and public acceptance of IoT-based fire safety systems will remain limited.

➤ *Standardization and Interoperability*

Another significant barrier to large-scale deployment is the lack of global standardization and interoperability among IoT fire detection systems. Presently, various manufacturers employ proprietary sensor designs, communication protocols, and data formats, resulting in fragmented and often incompatible systems [3], [15]. This inconsistency prevents seamless integration across different devices and platforms, thereby hindering scalability and maintenance.

The absence of universal standards for sensor calibration, data representation, and protocol interoperability complicates collaborative monitoring between multiple vendors or agencies in smart cities. For example, a building equipped with ZigBee-based detectors cannot easily share data with another system operating on NB-IoT or Wi-Fi, leading to isolated safety silos rather than an integrated response network [6], [11].

Standardization is essential to ensure consistent performance, interoperability, and security across global IoT deployments. International organizations such as IEEE, ITU, and ISO/IEC JTC 1/SC 41 have initiated efforts toward defining unified IoT communication frameworks and sensor interoperability standards. However, the fire detection domain still lacks domain-specific guidelines that address the unique challenges of environmental sensing, multi-sensor fusion, and emergency response coordination.

To bridge this gap, researchers and policymakers must work collaboratively to develop open-source communication frameworks and interoperable APIs that support cross-platform integration. Moreover, establishing compliance benchmarks for sensor precision, latency, and network reliability will enable fair comparison and certification across competing technologies.

➤ *Additional Challenges: Scalability and Real-Time Reliability*

Beyond these core challenges, ensuring scalability and real-time reliability is also critical for future IoT-based safety systems. Large-scale deployments involving thousands of sensors require efficient network management, adaptive bandwidth allocation, and load balancing to prevent latency during emergencies [10]. Furthermore, in mission-critical applications such as fire detection, even minor delays in communication or inference can have catastrophic consequences.

Techniques such as edge caching, priority-based scheduling, and QoS-aware routing must be optimized to maintain consistent performance under high data traffic. Future research should also explore self-healing networks and AI-driven fault detection mechanisms that can automatically isolate and recover from node failures in real time.

➤ *Summary*

While IoT-based multi-sensor fire detection systems have achieved remarkable progress, achieving energy autonomy, cyber resilience, and standardized interoperability remains the next major frontier. Addressing these challenges will be key to realizing the full potential of federated AIoT frameworks, enabling them to operate securely, efficiently, and reliably at city-scale deployment levels.

VI. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive study of IoT-enabled fire detection systems, emphasizing multi-sensor fusion, AI, and federated learning as key enablers for intelligent fire safety. The review of studies (2020–2024)

confirmed that combining heterogeneous sensors—such as temperature, smoke, gas, and infrared—significantly improves detection accuracy and reduces false alarms compared to traditional single-sensor designs [1], [4], [9].

A Secure Federated AIoT Framework was proposed, integrating NB-IoT/5G communication, MQTT protocol, and cloud–edge collaboration to ensure low latency, data privacy, and scalability in smart building environments. The framework unifies federated intelligence with real-time fire detection to enhance system reliability and efficiency.

Future work will focus on real-world prototyping, renewable-powered sensor nodes, and advanced secure federated learning algorithms to counter adversarial threats. Large-scale smart city trials will also be essential to validate interoperability and scalability.

By addressing these challenges, IoT-based multi-sensor systems can evolve into secure, adaptive, and intelligent platforms, capable of providing early, accurate, and reliable fire detection for modern infrastructures.

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