Development of a Low-Cost Early Fire Detection System with IoT and Telegram Integration

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Abstract. Urban fires remain a critical hazard in densely populated residential areas, often exacerbated by delayed detection and insufficient warning systems. This research aims to develop a low-cost, scalable fire detection system that leverages Internet of Things (IoT) technology and real-time messaging for rapid community-level alerts. The system was designed using ESP32 microcontrollers integrated with flame, gas (MQ-2) and temperature (DHT11) sensors, arranged in a Wireless Sensor Network (WSN) architecture. Sensor data are transmitted via Wi-Fi and MQTT to a central gateway, which instantly delivers alerts to residents through a Telegram bot. Field experiments were conducted across three homes, and the system achieved a detection accuracy of 97% with an average notification latency of 1.3 seconds. These results demonstrate that combining multi-sensor fusion with lightweight IoT communication ensures reliable detection and rapid notification. The findings indicate that the proposed solution is not only affordable but also adaptable for urban communities, addressing fire safety challenges where conventional alarm systems are ineffective. In conclusion, this work offers a practical and impactful strategy for enhancing community resilience and reducing high fire risks in high-density residential environments.

Keywords: Internet of Things, Wireless Sensor Network, MQTT, Telegram Bot, and Sensors.

1 Introduction

Urban fires continue to pose significant risks to communities worldwide. According to the National Fire Protection Association (NFPA), urban fire incidents account for billions of dollars in property damage and thousands of fatalities each year. Low-cost solution are essentials because many affected communities are low-income and cannot afford commercial fire alarm systems. Early detection is crucial to minimize casualties and property losses, as delays in fire warning often led to catastrophic outcomes. The Internet of Things (IoT) provides an effective platform for developing affordable, networked detection systems due to its ability to connect sensors, process data, and transmit alerts in real time [1]. Among various communication channels, Telegram integration offers a practical approach since it is widely accessible, lightweight, and capable

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of delivering instant notifications without requiring dedicated applications. In this context, developing a low-cost, IoT-based fire detection system with Telegram integration directly addresses the urgent need for scalable, real-time fire safety solutions in urban communities.

In Indonesia, densely populated neighborhoods are particularly vulnerable due to narrow streets, limited access to fire-fighting equipment, and the prevalence of aging electrical infrastructure. In such environments, early detection plays a critical role in reducing casualties and property loss.

Conventional fire alarms, while effective in controlled environments, often fail to address the specific needs of low-income urban communities. Limitations include high installation costs, lack of networked alert systems, and dependence on local alarm audibility, which can be ineffective during night time or when residents are away from home.

The emergence of Internet of Things (IoT) technology has opened new avenues for creating smart, networked fire detection systems. By combining low-cost microcontrollers, wireless networking, and cloud-based alert mechanisms, it is possible to create scalable solutions that overcome the shortcomings of traditional [1, 2].

This paper presents the design and implementation of a low-cost, scalable early fire warning system based on Wireless Sensor Network (WSN) architecture using ESP32 microcontrollers. The system integrates temperature, flame, and gas sensors, and utilizes a real-time alert mechanism via the Telegram messaging platform. Sensor data is transmitted wirelessly to a central gateway, which processes the input and sends emergency notifications when hazardous conditions are detected.

The proposed system aims to provide a proactive safety measure for densely populated residential areas, focusing on real-time awareness, affordability, and ease of deployment. Through testing and evaluation, this work demonstrates the practicality and effectiveness of IoT-based approaches in addressing fire safety challenges in urban environments.

2 Literature Review

IoT-based fire detection has become an active research area because of the availability of low-cost sensors and micro- controllers and the need for scalable early-warning in urban and remote environments. Early systems typically combined temperature and smoke sensors with cloud or local notification services; more recent work has focused on improving detection accuracy through multi-sensor fusion, lightweight machine learning on edge devices, and long-range low-power communications for wide-area coverage.

Several previous studies highlight the potential and limitations of IoT-based fire detection systems. Developed a cloud-connected fire monitoring system for dense residential areas, which demonstrated scalability but relied on higher-cost hardware, limiting its adoption in low-income settings [3]. Proposed integrating IoT technology into residential building design, providing continuous monitoring but restricting applicability mainly to newly constructed buildings [4]. Implemented a low-cost logistic regression model for real-time fire detection in smart cities, achieving improved accuracy over simple thresholding but with limited real-world testing [5]. Introduced FireNet-v2, a lightweight deep learning model for IoT applications, which achieved high accuracy but required more computational resources, making it unsuitable for low-cost community deployments [2]. Finally, demonstrated the use of embedded machine learning for fire detection on microcontrollers, reducing latency but increasing firmware complexity [6]. In contrast, our work extends these studies by combining multi-sensor fusion (temperature, flame and gas) with a cost-efficient ESP32 platform and a simple, real-time Telegram alert system. Unlike ML-heavy of high-cost solutions, our approach emphasizes affordability, ease of deployment, and community level scalability, while maintaining high accuracy validated through field experiments.

To improve detection robustness, researchers have explored integrating multiple sensing modalities (e.g., temperature, gas, flame, humidity) with statistical or ML-based anomaly detection. Logistic regression and anomaly detection methods have been applied to reduce false alarms in urban deployments, while embedded ML and computer vision approaches have been proposed for camera-equipped environments. Although such methods can boost accuracy, they may increase computational and privacy costs. A comprehensive review of deep- learning approaches for fire and smoke detection highlights trade-offs between accuracy and computational requirements, particularly for real-time edge applications [7-8].

For large-scale or remote monitoring, LoRa/LoRaWAN and other LPWAN technologies have been utilized to extend coverage beyond Wi-Fi range. LoRa-based systems typically transmit periodic temperature, humidity, and particulate/smoke data to gateways, enabling kilometer-scale monitoring at low power. These solutions are effective for outdoor and inter- community deployments but require careful calibration to minimize false positives from environmental variation [9-10]. Recent research has emphasized edge intelligence and trust-aware detection. Lightweight embedded ML and hybrid edge/cloud models can improve detection performance while reducing network load, and ensemble or trust-driven approaches help filter out false positives from non-fire sources such as sunlight or cooking smoke. Evaluations in the literature show that combining sensor fusion with simple ML classifiers or thresholding heuristics yields reliable detection for low-cost, real-time deployments [6].

Identified gaps: Many surveyed solutions (a) rely solely on simple thresholding with limited real-world testing, (b) employ computationally intensive ML models unsuitable for very low-cost nodes, or (c) use long-range networks without community-level integration.

This work addresses these gaps by designing a hybrid solution that uses multi-sensor fusion (flame, gas, temperature) for improved accuracy. Implements instant Telegram-based alerts without requiring dedicated mobile applications. Optimizes for low-bandwidth, low-cost, community-level deployment.

Evidence from recent reviews and implementations supports this low-cost, edge-capable strategy as both timely and relevant [3]. Compared with existing solutions, developed a cloud-connected fire monitoring system for dense residential areas but relied on higher-cost hardware [3]. Proposed integrating IoT into building design for fire risk monitoring, focusing primarily on architectural applications [4]. Implemented low-cost detection using logistic regression but with limited real-world testing [5]. Introduced FireNet-v2, a lightweight deep-learning model for real-time detection, but its computational requirements were unsuitable for low-cost deployments [2].

Several IoT-based fire detection systems from prior research are summarized in Table 1, highlighting their hardware platforms, communication methods, strengths, and limitations. Developed a cloud-connected fire monitoring system for dense residential areas but relied on higher-cost hardware [3]. Proposed integrating IoT into building design for fire risk monitoring but focused primarily on architectural applications [4]. Implemented low-cost detection using logistic regression but with limited real-world testing [5]. Introduced a lightweight deep learning model (FireNet-v2) for real- time detection, yet it required higher computational resources unsuitable for low-cost deployments [2]. Other works have explored multi-sensor threshold fusion for reliable detection at low power consumption, LoRaWAN-based designs for long-range forest fire detection and embedded ML on microcontrollers for reduced latency [6, 8-9]. While these solutions demonstrate various strengths ranging from scalability to precision, they also face limitations, such as susceptibility to environmental noise, high firmware complexity, or lack of indoor/urban optimization.

Table 1. Comparative summary of existing IoT-based fire detection.

Study & Year	Technology & Hardware	Communication	Pros	Cons
Muhendra & Amin (2022)	IoT + sensors, cloud integration	Cloud Messenger	Centralized monitoring, scalable	Higher hardware cost
Abdullahi et al. (2025)	IoT in building design	Wi-Fi	Architectural integration, continuous monitoring	Limited to new building projects
Said et al. (2024)	Logistic regression + sensors	Wi-Fi	Low cost, improved detection accuracy over thresholding	Limited dataset, urban only
Shees et al. (2023)	FireNet-v2 DL model	IoT	High accuracy, real-time	Higher computational load, needs camera/special sensors
Vasconcelos et al. (2023)	Multi-sensor + threshold fusion	Varies	Reliable detection, low power	Susceptible to environmental noise
Sulaiman et al. (2021)	Temp, smoke sensors	LoRaWAN	Long range, low power	Not optimized for indoor/urban

Table 1 (Continued). Comparative summary of existing IoT-based fire detection.

Study & Year	Technology & Hardware	Communication	Pros	Cons
Peruzzi et al. (2023)	ML on micro-controllers	Wi-Fi / LoRa	Edge processing, reduced latency	Higher firmware complexity
This Work (2025)	ESP32 + multi-sensor +Telegram	Wi-Fi + MQTT	Low cost, real-time community alerts, easy to deploy	Range limited to Wi-Fi coverage

Positioned within this context, this work combines the low-cost, multi-sensor capabilities of ESP32-based nodes with the scalability of MQTT communication and the immediacy of Telegram alerts. As shown in Table 1, our approach addresses the identified research gaps by balancing affordability, responsiveness, and ease of community-level deployment, while avoiding the excessive computational demands and infrastructure costs seen in some prior solutions.

3 Method

3.1 Requirement Analysis

Key fire hazards were identified through a literature review and community feedback, revealing that most local fire incidents involved overheating, gas leaks, and open flames. Based on the National Fire Protection Association (NFPA) guidelines and sensor datasheet specifications, detection thresholds were set to 35 °C for temperature and 300 ppm for gas concentration.

3.2 System Design

The proposed system adopts a Wireless Sensor Network (WSN) architecture as shown as Fig. 1 comprising multiple ESP32-based sensor nodes that transmit data to a central gateway.

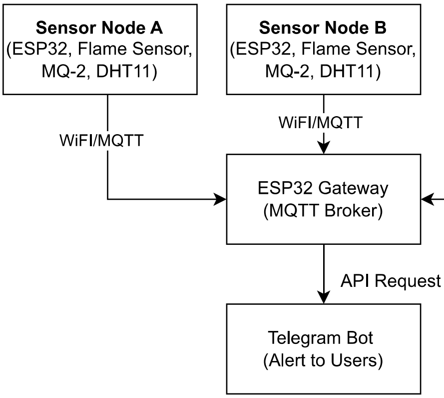

Fig. 1. System architecture of the proposed IoT based early fire detection system.

3.3 Hardware Development

Prototype nodes were assembled on breadboards using cost-optimized components to minimize production expenses. Each node included a buzzer for local alerting in addition to wireless notifications.

3.4 Firmware and software

Firmware was developed using the Arduino IDE. The gateway operated as an MQTT broker and executed threshold-based logic to process sensor readings. When any parameter exceeded its predefined threshold, the gateway simultaneously activated the local buzzer and sent a Telegram message to registered users. The decision-making process follows the workflow shown in Fig. 2, where the system continuously acquires sensor data, compares it to predefined thresholds, and triggers alerts when hazardous conditions are detected.

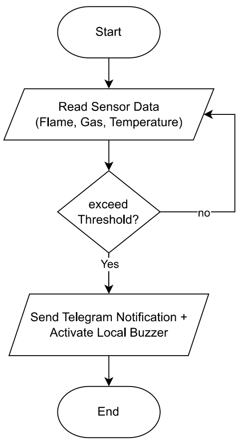

Fig. 2. Workflow of the fire detection and notification process.

3.5 Testing Procedure

The system was evaluated under controlled fire hazard simulations designed to represent realistic urban household risks. Three sensor nodes were deployed in three different homes; each located in densely populated neighborhoods. Simulated events include: (1) controlled open flames using a candle and lighter, (2) gas leaks using liquefied petroleum gas (LPG) sources, and (3) elevated heat resources such as electric stoves and heaters. Each event was repeated 10 times per nodes (N=30 trias per event tupe, 90 events total) to ensure consistency. Environmental conditions included indoor setting with room size between 12-16 m^2 and natural ventilation. Prior to testing, sensors were calibrated by recording baseline values for 24 hours under normal indoor conditions to confirm thresholds of 35°C for temperature and 300 ppm for gas concentration. Performance metrics included detection accuracy, notification latency and user response time.

The system's modular design allows easy adaptation and expansion for different urban community environments. The solution is designed with modularity in mind, allowing for easy expansion and adaptation across various urban communities.

4 Results and Discussion

4.1 Detection Performance

Field testing was carried out on three sensor nodes deployed in separate homes. Under simulated fire conditions, including controlled gas leaks, open flames, and elevated temperatures, the system achieved a detection accuracy of 97% (see Table 2). All three sensors, temperature, gas, and flame, provided consistent readings within expected operating tolerances, confirming the reliability of hardware and threshold-based logic.

Table 2. Detection performance thresholds and parameters used for triggering alerts.

Parameter	**Threshold Value**
Temperature	>35
Gas Level	200 ppm
Flame	Detected

4.2 Sensor Data Analysis

Data collected during the test period are summarized in Table 3. Normal operating conditions showed temperature readings well below the 35°C threshold and gas concentrations below 300 ppm. When open flames or gas leaks were introduced, sensor readings spiked sharply, triggering alerts (see Table 3).

Table 3. Recorded sensor readings from three ESP32-based nodes during the test period, including temperature, gas concentration, flame detection status, and corresponding alert/notification outcomes.

Timestamp	**Node ID**	**Temp (°C)**	**Gas (ppm)**	**Flame**	**Alert Trig-gered**	**Tele-gram Sent**
2025-07-29 12:14:00	Node A	29.3	180	0	No	No
2025-07-29 12:15:00	Node B	29.5	210	1	Yes	Yes
2025-07-29 12:16:00	Node C	29.8	169	0	No	No
2025-07-29 12:17:00	Node A	29.6	185	0	No	No
2025-07-29 12:18:00	Node B	29.7	220	1	Yes	Yes
2025-07-29 12:19:00	Node C	30.0	175	0	No	No
2025-07-29 12:22:00	Node C	30.7	230	1	Yes	Yes
2025-07-29 12:23:00	Node A	30.1	180	0	No	No
2025-07-29 12:24:00	Node B	29.9	260	1	Yes	Yes
2025-07-29 12:25:00	Node C	30.4	240	0	No	No
2025-07-29 12:26:00	Node A	30.8	170	0	No	No
2025-07-29 12:27:00	Node B	31.2	195	1	No	Yes
2025-07-29 12:28:00	Node C	31.5	300	0	Yes	Yes

Fig. 3. Illustrates the temperature variations over time for each node, showing stable baseline readings and clear spikes during simulated fire events. Fig. 4 presents gas concentration levels over the same period, with noticeable peaks coinciding with hazardous scenarios. In most events, flame detection occurred simultaneously with elevated temperature and gas readings, reinforcing the benefit of multisensory fusion in reducing false positives.

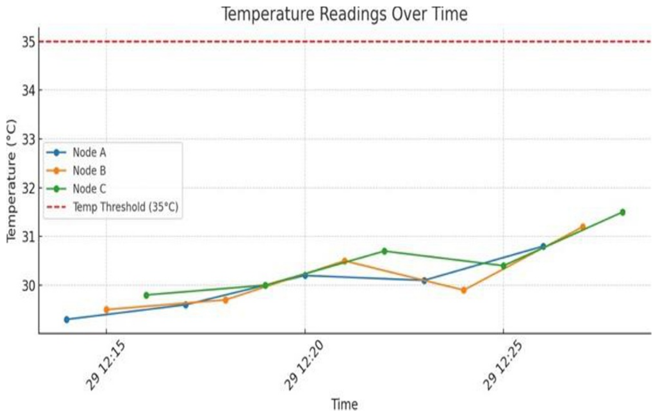

Fig. 3. Temperature readings over time for each sensor node, showing stable baseline values and sharp increases during simulated fire events.

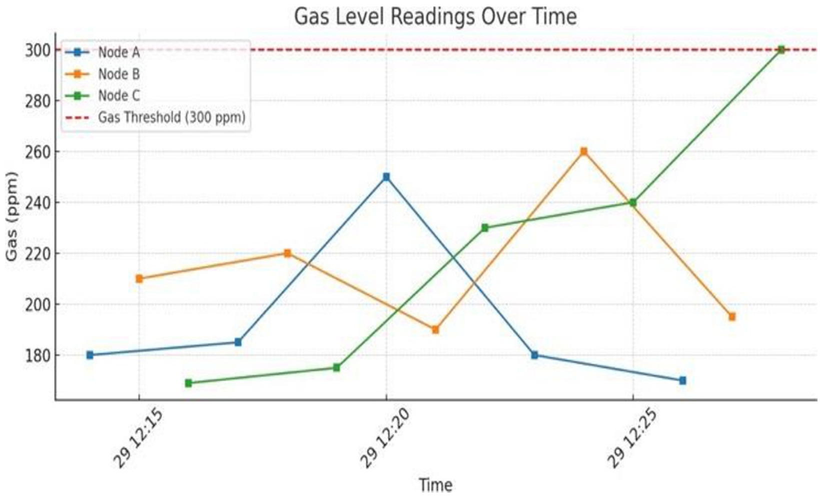

Fig. 4. Gas concentration readings over time for each sensor node, with peaks corresponding to hazardous conditions and flame detection events.

4.3 Notification Latency

The average delay between hazard detection and Telegram alert delivery was 1.3 seconds, measured over multiple trials. This latency is within acceptable limits for real-time community-level warning systems and remains consistent across all nodes. Fig. 5 compares the detection-to-notification latency for each node, illustrating minimal variation between devices and confirming consistent alert delivery performance.

Fig. 5. Detection latency across three ESP32-based nodes during simulated fire events, showing consistent average notification delays of approximately 1.3 seconds.

4.4 Community Feedback

Residents confirmed that Telegram alerts were received promptly and reported that the local buzzer provided an effective supplementary warning, particularly useful during internet disruptions. This dual-alert approach enhances both reliability and accessibility of the system.

An example of the Telegram notification received by users is shown in Fig. 6, which displays the hazard type, timestamp, and location information. This format was reported by participants as clear and actionable, enabling rapid response during simulated fire events.

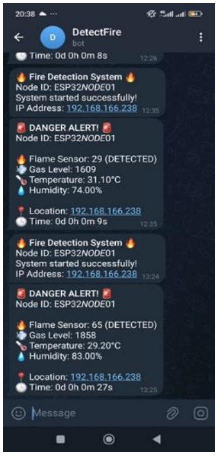

Fig. 6. Example of a Telegram notification sent by the proposed IoT-based fire detection system, showing hazard type, timestamp, and location details as received by users during testing.

4.5 Discussion

The results highlight the practicality and reliability of the proposed IoT-based fire detection system. Compared with prior works, this system achieved a 97% detection accuracy and an average alert latency of 1.3 seconds. For example, implemented logistic regression for fire detection in smart cities, which improved accuracy over simple thresholding but lacked real-world validation. Our results extend this by validating performance under realistic conditions in residential homes. Introduced FireNet-v2, a lightweight deep learning model for IoT applications that achieved high accuracy but required more computational resources, making it unsuitable for low-cost community deployments. In contrast, our threshold-based approach demonstrated similar reliability while maintaining low hardware complexity. That embedded ML could reduce latency, but their systems required higher firmware complexity [6]. Our work demonstrates that simple multi-sensor fusion with MQTT communication can achieve comparable latency with less computational overhead. Focused on cloud-integrated or architectural IoT systems, but their solutions either relied on expensive hardware or were limited to new building projects [3]. In comparison, our system is affordable, adaptable, and deployable in existing low-income housing.

Community feedback further confirmed the usability of the system. Residents reported that the Telegram alerts were clear, timely, and actionable, while the local buzzer provided an additional safeguard during connectivity issues. This dual-alert mechanism distinguishes our work from prior studies that relied solely on internet-based notifications.

Overall, the proposed system balances affordability, responsiveness, and reliability more effectively than existing solutions. While some ML-based systems may offer marginal accuracy improvements, their higher cost and complexity limit adoption in the target communities. Thus, our findings suggest that a carefully optimized multi-sensor IoT system can achieve practical fire safety impact at community scale.

4.6 Limitations

Despite promising results, this study has several limitations. First, the system was tested only in three homes with a limited number of trials; larger-scale deployments are needed to validate performance across diverse environments. Second, detection relies on predefined threshold, which may not adapt to varying environmental conditions. Third, the system is restricted to Wi-Fi coverage and depends on internet connectivity for Telegram alerts, which may not be reliable in all communities. Finally, the evaluation was limited to indoor residentials settings and did not include outdoor or industrial fire scenarios.

5 Conclusion

This paper presented the design, implementation, and evaluation of a low-cost IoT-based early fire warning system integrating ESP32 microcontrollers, multi-sensor detection (flame, gas, temperature), and Telegram-based real-time notifications. The results show that multi-sensor fusion combined with lightweight MQTT communication enables accurate and rapid-fire detection without the high computational costs associated with ML-heavy solutions. While the system's current range is limited to Wi-Fi coverage, its modular architecture allows for integration with extended-range technologies. Future work will focus on Implementing machine learning models for predictive detection. Deploying solar-powered sensor nodes for off-grid areas. By combining affordability, scalability, and rapid alerting, the proposed system offers a practical solution for enhancing fire safety in densely populated urban environments.

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