Green Intelligent Systems and Applications

Research Article
Volume 6(1), 2026, 19−33
https://doi.org/10.53623/gisa.v6i1.1009

An Image Processing-Based Fire Detection System Using Orange Pi 4A with Internet of Things Integration in Indoor Environments

Safeti Intan Pratiwi*, Eka Puji Widiyanto

Faculty of Computer Science and Engineering, Electrical Engineering Study Program, Universitas Multi Data Palembang, South Sumatra, Indonesia

Correspondence: safetiintanpratiwi_2226270020@mhs.mdp.ac.id

SUBMITTED: 24 January 2026; REVISED: 14 February 2026; ACCEPTED: 19 February 2026

ABSTRACT: Fire hazards in indoor industrial environments require fast and reliable detection systems, as conventional sensor-based methods often suffer from delayed responses and high false-alarm rates. This study proposes a low-cost, Internet of Things-integrated visual fire detection system based on the YOLOv11 deep learning model implemented on an Orange Pi 4A. The system integrates an IP camera for visual acquisition, real-time detection, and automatic data logging through a MySQL-based monitoring platform. Experiments were conducted in a 3 × 3 m indoor environment using candle, stove, and burning fires at various camera distances. System performance was evaluated using confidence score, bounding box pixel area, and recall based on True Positive and False Negative classifications. Candle flames were reliably detected up to 100 cm with recall values of 90.24%–100% and pixel areas below 5,000 px, while stove flames achieved recall above 93% at 50–100 cm with pixel areas of 11,144–42,525 px. Burning fires maintained high performance up to 300 cm, reaching confidence values above 0.70 and recall rates of 78.94%–100% with pixel areas exceeding 44,000 px. The results indicate that detection reliability is primarily influenced by apparent flame size rather than camera distance. Overall, the proposed system demonstrates strong feasibility as an embedded, IoT-integrated fire detection solution for early warning in indoor industrial environments, although limitations remain in detecting small flames under low-resolution and low-light conditions.

KEYWORDS: Fire detection; YOLOv11; Orange Pi 4A; computer vision; internet of things; indoor safety

1. Introduction

Fire hazards remained one of the most serious safety threats in industrial environments, particularly in facilities involving electrical machinery, combustible materials, and high-temperature production processes. Undetected or late-detected fire incidents could lead to severe consequences, including infrastructure damage, production interruption, and risks to human safety [1–3]. Therefore, the development of reliable and fast fire detection systems was essential to enhance occupational safety and minimize potential losses in industrial areas.

Conventional fire detection technologies, such as smoke detectors, heat sensors, and point flame sensors, were widely applied in industrial settings. These systems detected chemical or physical changes caused by fire, including smoke concentration and temperature rise, and triggered alarms when predefined thresholds were exceeded. However, such approaches exhibited inherent limitations. Smoke detectors often responded slowly due to delayed smoke accumulation, heat sensors activated only after significant temperature increases, and flame sensors required unobstructed lines of sight and were sensitive to environmental disturbances such as dust and light reflections [4–6,16,17]. In addition, conventional sensor-based systems were prone to false alarms and required regular calibration and maintenance, which increased operational costs and reduced long-term reliability.

In contrast, vision-based fire detection systems utilized cameras and image processing algorithms to analyze visual features such as flame color, motion patterns, and smoke characteristics directly from video streams. Previous studies demonstrated that camera-based approaches provided wider monitoring coverage, earlier detection, and better situational awareness compared to point sensors [18–20]. However, most existing systems focused on algorithm performance on desktop computers, while practical implementation on embedded devices with Internet of Things-based monitoring in industrial environments remained limited.

Recent advances in deep learning significantly improved the performance of visual fire detection systems. Convolutional Neural Networks and real-time object detection frameworks, particularly the You Only Look Once (YOLO) algorithm, achieved high accuracy and low latency in detecting fire and smoke in video streams [9–12]. The integration of these models with single-board computers enabled automated alert generation, real-time monitoring, and remote access while maintaining reasonable processing efficiency, which was critical for industrial safety applications [13–15,21].

Despite these advances in deep learning-based fire detection, a clear research gap remained. While previous studies demonstrated the effectiveness of YOLO-based models, limited attention was given to their real-time integration with Internet of Things platforms on embedded hardware suitable for continuous industrial monitoring. Furthermore, only a few studies systematically analyzed the relationship between bounding box pixel area, confidence score, detection distance, and recall performance in practical indoor environments. As a result, comprehensive embedded vision-based fire detection systems with integrated monitoring and analytical evaluation remained limited.

To address this gap, this study proposed an image processing-based fire detection system using YOLOv11 implemented on an Orange Pi 4A with Internet of Things integration. The proposed system enabled real-time visual detection, fire severity classification, and automated data logging through a centralized database. The system was evaluated in a controlled indoor environment using a single camera. Although this setup ensured experimental consistency, limitations remained in terms of sensitivity to small flames and lighting variations. By addressing both detection accuracy and embedded system efficiency, this study contributed to the development of practical, IoT-integrated fire detection systems for industrial safety monitoring.

2. Materials and Methods

This study employed an experimental research design to develop and evaluate an Internet of

Things-based visual fire detection system using embedded hardware and computer vision techniques. The proposed system integrates visual data acquisition, real-time image processing, and automatic warning mechanisms to enable early fire detection in indoor industrial environments. System implementation and testing were conducted in a controlled 3× 3 m indoor room to ensure consistent experimental conditions.

2.1. System architecture.

The proposed fire detection system consisted of three main components: a visual sensing unit, a central processing unit, and an Internet of Things-based monitoring subsystem. Visual data were acquired using an IP camera connected to the Orange Pi 4A via Ethernet or Wi-Fi within the same local network. The camera continuously streamed video frames for real-time analysis. The system architecture was organized into four main functional modules: visual sensing, YOLOv11-based processing, IoT data logging, and alarm output. The Orange Pi 4A processed incoming frames using a YOLOv11-based fire detection model to generate bounding box coordinates, pixel area measurements, and confidence scores. When detected fire objects exceeded predefined danger thresholds, an audible buzzer was automatically activated to provide immediate local warnings. Detection results were transmitted in real time through the local network and stored in a MySQL database with time stamps. Under stable local network conditions, this approach enabled continuous monitoring and structured data logging, although temporary network interruptions could affect data completeness. The overall system workflow, including visual sensing, processing, IoT logging, and alarm output, was illustrated in Figure 1.

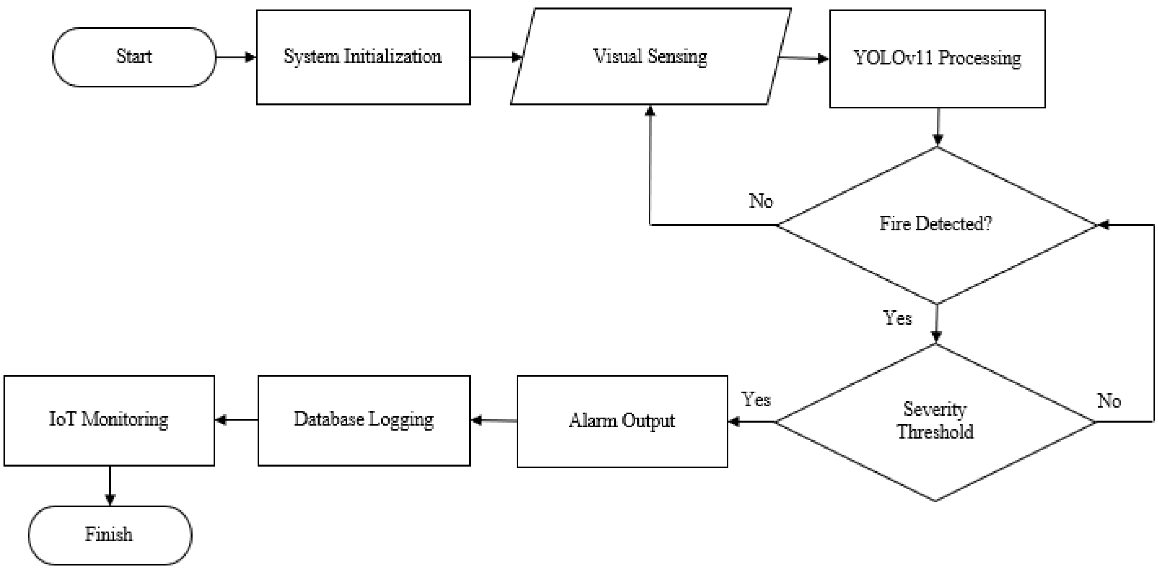
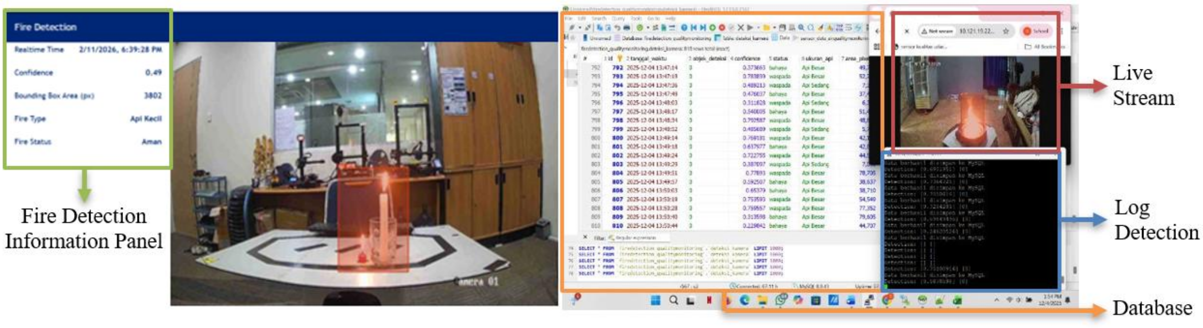


Figure 1. Flowchart of the system operation.

Furthermore, the transmitted detection data were visualized through an IoT-based monitoring interface that enabled real-time system supervision. As shown in Figure 2, the interface consisted of a live video display panel, real-time detection logs, fire severity status indicators (Safe, Alert, and Danger), confidence score information, and system connectivity status. This unified dashboard allowed operators to continuously monitor fire conditions, detection results, and system responses remotely.



(a) (b)

Figure 2. IoT Monitoring interface (a) Dashboard monitoring (b) System testing interface.

2.2. Hardware components.

The proposed fire detection system was implemented using an Orange Pi 4A as the central processing unit, one IP camera for visual data acquisition during experimental testing, an active buzzer for local alerts, and a regulated power subsystem. The Orange Pi 4A executed the YOLOv11-based fire detection algorithm, processed real-time video streams from the IP camera, transmitted detection results through the IoT communication layer to a monitoring interface and database, and controlled alarm activation. Although the system architecture supported multi-camera deployment for wider-area monitoring, the experimental evaluation in this study was conducted using a single IP camera due to the limited size of the indoor test environment (3 × 3 m), which provided sufficient visual coverage. The buzzer was triggered programmatically when detected fire events exceeded the predefined danger threshold. The power subsystem converted AC 220 V input into a regulated 12 V DC supply, which was further stepped down to 5 V DC using an XL4005 regulator module to ensure voltage stability and protect all system components. The electrical schematic of the proposed system was shown in Figure 3, illustrating the interconnection between the power supply, Orange Pi 4A, IP camera, and alarm device.

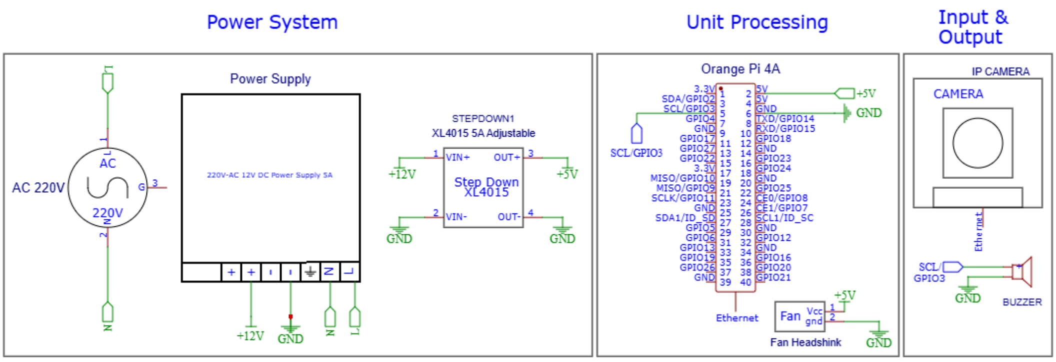


Figure 3 Fire detection system schematic.

2.3. Software environment and YOLOv11-based fired detection.

The proposed system employed a YOLOv11 deep learning model to perform real-time fire detection from video streams captured by the IP camera. For each detected fire object, the model output a bounding box defined by its center coordinates and dimensions, namely width (w) and height (h), expressed in pixel units. These bounding box parameters provided spatial localization of the detected fire region within each video frame, enabling subsequent quantitative analysis.

To quantify the apparent visual size of the detected fire, the bounding box width and height were used to calculate the pixel area (A) of the fire region, as expressed in Equation (1).

$$A = w \; x \; h \qquad (1)$$

The pixel area represented the spatial extent of the detected fire and reflected the amount of visual information available for detection. This size-related feature was particularly relevant in vision-based fire monitoring systems operating on embedded platforms, where computational efficiency and detection reliability were critical. The use of bounding box area as an object size indicator was a common practice in real-time object detection, as spatial extent was often correlated with detection confidence and object significance [22].

In addition to spatial features, the YOLOv11 model also produced a confidence score for each detected fire object, indicating the probability that the detected region corresponded to an actual fire event. Based on the combined evaluation of bounding box pixel area and confidence score, detected fires were classified into three visual fire scale levels, namely small, medium, and large. The classification criteria, corresponding system status, and alarm responses were summarized in Table 1. The adopted pixel area and confidence thresholds were empirically determined through preliminary experiments by considering camera resolution, detection stability, and practical safety requirements in real-world indoor environments.

Table 1 Decision rules for fire severity classification and alarm activation.

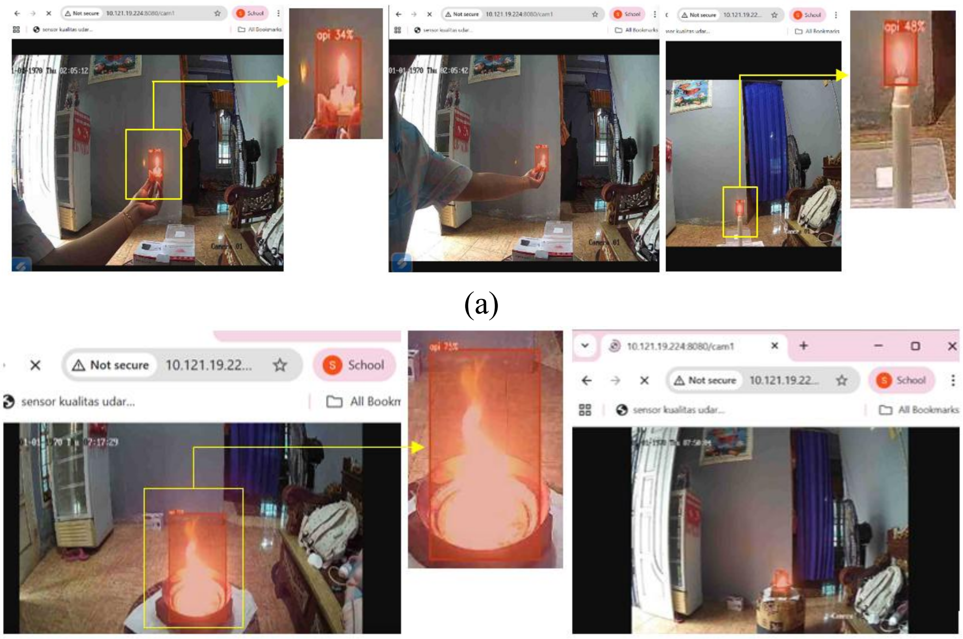
Fire Scale	Bounding Box Pixel Area (A)	Confidence Score (%)	Expected System Response	Alarm Action
Small Fire	A < 5.000 pixels	0.20 Confidence ≤ 0.50	Safe	No Alarm
Medium Fire	5.000 ≤ A ≤ 20.000 pixels	0.50 < Confidence ≤ 0.70	Alert	Dashboard Notification
Large Fire	A > 20.000 pixels	Confidence > 0.70	Danger	Buzzer

The pixel area and confidence thresholds presented in Table 1 were derived empirically through preliminary experiments conducted using the same camera resolution (800 × 600 pixels) and YOLOv11 detection configuration applied in the main system implementation. During initial testing, bounding box outputs and confidence scores were continuously monitored through the real-time detection log to evaluate detection stability. Experimental results indicated that bounding box areas below approximately 5,000 pixels were frequently associated with unstable detections and fluctuating confidence values, particularly for small flames at longer distances. Pixel areas between 5,000 and 20,000 pixels produced consistent detections with confidence scores exceeding the predefined threshold (0.2), while areas larger than 20,000 pixels were typically linked to dominant fire regions with high detection reliability. In addition to spatial features, the YOLOv11 model generated a confidence score representing the probability of a true fire event. This value reflected detection reliability and was influenced by factors such as flame visibility, lighting conditions, and background complexity. Therefore, pixel area and confidence score were jointly used as primary indicators for fire severity classification and alarm decision-making. However, these threshold values were dependent on camera resolution, viewing distance, and environmental lighting conditions. Consequently, different deployment environments might require recalibration to maintain detection reliability.

2.4. Experimental setup and data collection.

The experimental evaluation was conducted in the same indoor test environment described in

Subsection 2, Material & Methods. The IP camera was mounted at a height of 200 cm with an approximate horizontal field of view of 90°, ensuring consistent frontal observation of the fire sources. All experiments were performed under normal indoor lighting conditions, with illumination levels ranging from 250 to 400 lux. Two primary testing scenarios were designed to assess the performance of the proposed fire detection system based on the visual parameters and decision rules described in Subsection 2.3. The first scenario focused on distance variation, in which the distance between the camera and the fire source was gradually increased until detection performance degraded or fire objects were no longer detectable. The second scenario evaluated detection consistency under different fire source types and visual characteristics. Controlled fire sources, including candle flames, stove flames, and combustion flames, were used to represent typical indoor fire conditions. These sources were employed to generate variations in flame size, intensity, and visual patterns at different observation distances. The purpose of these variations was to evaluate the system's response to changing visual fire characteristics rather than to directly determine fire scale. Figure 4 illustrated representative detection results obtained during the experiments, showing variations in bounding box size and confidence score at different fire scales. These examples demonstrated how spatial localization and detection reliability changed as fire size increased, thereby supporting the validation of the pixel area and confidence thresholds defined in Table 1.



(a)

(c) (b)

Figure 4 Examples of real-time fire detection results at different fire scales (a) small fire, (b) medium fire, and (c) large fire, showing bounding box localization and confidence values.

Each experimental trial was conducted for approximately 15–20 minutes for each fire source type to observe the quantity, stability, and consistency of detection results. During the experimental period, a total of 556 valid detection samples were collected from all test scenarios, covering different fire source types and observation distances. All valid detection outputs were transmitted through the Internet of Things communication system and automatically stored in a MySQL database with time stamps, enabling structured data logging and real-time performance analysis within fixed time intervals of 30–60 s. To ensure data reliability, timestamp-based logging and automatic reconnection mechanisms were implemented to minimize the impact of temporary network delays or transmission errors. The collected dataset consisted of time-stamped detection records, including detection response time, confidence scores, bounding box pixel areas, detection consistency, and detection frequency within fixed time intervals of 30 s, which were used to characterize the temporal and spatial behavior of the fire detection system [7,13].

2.5. Performance evaluation metrics.

The experimental results were analyzed using quantitative performance metrics to evaluate the effectiveness and reliability of the proposed fire detection system. The evaluation focused on detection accuracy, classification reliability, and stability under different observation distances and fire source conditions. System performance was primarily assessed using True Positive (TP) and False Negative (FN) metrics. A detection result was categorized as a True Positive (TP) when the predicted fire severity level correctly corresponded to the actual visual condition of the fire source based on the predefined thresholds in Subsection 2.3, consistent with evaluation approaches reported in previous YOLO-based fire detection studies [23]. Conversely, a detection was considered a False Negative (FN) when the system failed to detect a fire or misclassified its severity level, particularly in cases involving low confidence scores or incorrect hazard categorization. Based on TP and FN values, recall was adopted as the main evaluation indicator to measure the system's capability to minimize missed detections, which was critical for early warning applications [1,8]. Recall was calculated as follows:

$$Recall = \frac{TP}{TP + FN} \qquad (2)$$

where TP represents correctly classified fire detections and FN represents missed or severity-misclassified detections.

To evaluate detection stability and consistency, repeated experiments (5–7 trials) were conducted under identical conditions at each observation distance. Detection stability was quantified using the sample standard deviation, calculated as [24]:

$$\sigma = \sqrt{\frac{\sum(X_i - X')^2}{N-1}} \qquad (3)$$

where $X_i$denotes individual measurement values, $\bar{X}$is the sample mean, and N represents the number of samples.

In addition to recall and stability analysis, alarm decision accuracy was evaluated by correlating confidence scores and bounding box pixel areas with predefined fire severity thresholds. This analysis aimed to examine the relationship between visual fire characteristics, detection confidence, and classification reliability. All performance indicators were computed based on the time-stamped detection records stored in the database, ensuring objective and reproducible evaluation [7,13]. The obtained results were further analyzed in relation to fire size variation and observation distance to assess system robustness in practical indoor monitoring scenarios.

3. Results and Discussion

The fire detection system was evaluated using two IP cameras operating simultaneously in the same room to assess the performance of the YOLOv11 model under a multi-camera configuration. The evaluation considered fire size, object distance, and confidence score thresholds, with analysis focusing on average confidence, fire status classification, and True Positive Rate, demonstrating the system's ability to detect fires of varying sizes across different camera perspectives.

3.1. Results of fire detection using IP camera.

Fire detection testing on the IP cameras was conducted using candle, stove, and combustion flames as detection objects to evaluate how the computer vision system classified fires as small, medium, or large scale based on visual perception at varying distances from 50 cm up to the maximum detectable range of the camera.

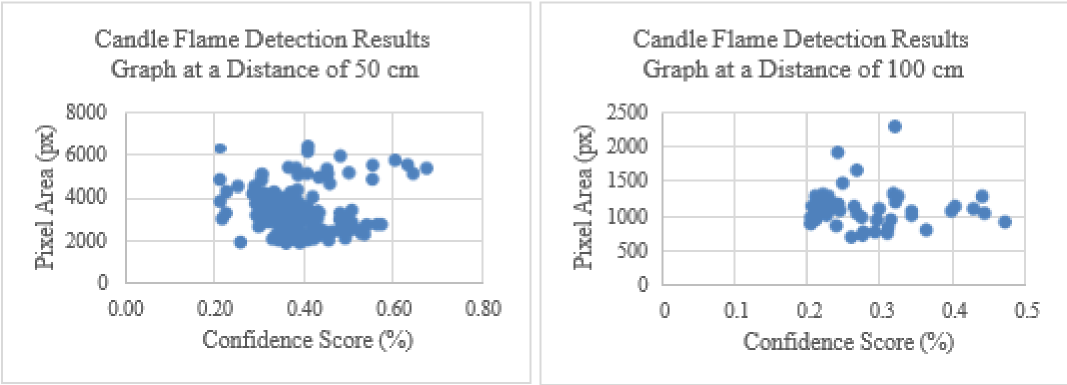
3.1.1. Candle Flame.

Table 1 summarized the candle flame detection performance of the IP camera at varying distances, reporting the average and standard deviation of confidence scores, bounding box pixel areas, and recall. Based on the candle flame detection results using IP Camera 1 (Table 1), the system showed performance variations driven by changes in the apparent visual size of the flame at different camera distances. At 50 cm, the average confidence was 0.39 (SD = 0.085) with an average bounding box area of 3,252 px (SD = 1,051 px), resulting in a recall of 90.24%, indicating stable detection when the flame occupied a sufficient visual area. At 100 cm, the average confidence decreased to 0.27 (SD = 0.070) and the average pixel area to 1,090 px (SD = 2,869 px); however, the system achieved a recall of 100%, showing that all samples were successfully detected despite the reduced visual size. At 150 cm, no detections were recorded, indicating that the flame became too small to be resolved by the camera. Overall, the results confirmed that detection reliability was primarily influenced by the apparent visual size of the flame rather than by camera distance alone.

Table 1. IP CAMERA candle flame detection test results.

Distance (cm)	No. of Sample	Confidence Score (%)		Pixel Area (px)		TP	FN	Recall (%)	Fire Class
		Avg	SD	Avg	SD				
50	164	0.39	0.085	3.252	1.051	148	16	90.24	Small Fire
100	48	0.27	0.070	1.090	2.869	48	0	100	Small Fire
150	0	0	0	0	0	0	0	0	Not Detected

Figure 4 showed a scatter plot of fire detection confidence scores versus bounding box pixel areas for detected candle flames at distances of 50 cm and 100 cm. Most data points fell within a confidence range of 0.30–0.50 and a pixel area range of approximately 2,000–5,000 pixels, indicating stable detection when the flame was clearly visible and remained within the predefined small-fire visual scale. Several outliers at 50 cm, with pixel areas exceeding 6,000 pixels, were attributed to natural flame shape and brightness fluctuations. Overall, a positive correlation was observed between pixel area and confidence score, confirming that detection reliability increased with larger apparent flame size and remained stable at moderate distances.



(a) (b)

Figure 4. Relationship between confidence value and the size of the pixel area of candle flame detection (a) Distance 50 cm (b) Distance 100 cm.

3.1.2. Stove fire.

Table 2 summarized the stove flame detection performance of the IP camera at varying distances, reporting the average and standard deviation of confidence scores, bounding box pixel areas, and recall. The stove flame detection performance using IP Camera 1 varied with camera distance (Table 2). At 50 cm, the system achieved an average confidence of 0.56 (SD = 0.18) and a bounding box area of 42,525 px (SD = 20,490 px), resulting in a recall of 96.87%. At 100 cm, detection remained reliable with similar confidence (0.56, SD = 0.11) and a reduced pixel area of 11,144 px (SD = 2,440 px), yielding a recall of 93.50%. Beyond 100 cm, performance decreased sharply: at 150 cm, confidence dropped to 0.44 (SD = 0.14) with a pixel area of 3,316 px (SD = 1,446 px) and a recall of 10.71%, while at 200 cm, confidence and pixel area further declined to 0.40 (SD = 0.10) and 2,476 px (SD = 648 px), respectively, with a recall of 3.33%. No detections were recorded at 250 cm. These results indicated that reliable stove flame detection was limited to distances below 1 m, where the flame occupied sufficient visual area for stable recognition. Based on bounding box size and detection stability, the stove flame was classified as a medium-scale fire, producing larger and more consistent pixel areas compared to small-scale sources such as candle flames.

Table 2. IP CAMERA stove flame detection test results.

Distance (cm)	No. of Sample	Confidence Score (%)		Pixel Area (px)		TP	FN	Recall (%)	Fire Class
		Avg	SD	Avg	SD				
50	64	0.56	0.18	42.525	20.490	62	2	96.87	Medium Fire
100	77	0.56	0.11	11.144	2.440	72	5	93.50	Medium Fire
150	28	0.44	0.14	3.316	1.446	3	25	10.71	Small Fire
200	15	0.40	0.10	2.476	648	5	10	3.33	Small Fire
250	0	0	0	0	0	0	0	0	Not Detected

Figure 5 showed scatter plots at distances of 50–200 cm, illustrating a consistent relationship between detection confidence and bounding box pixel area. At 50–100 cm, most data points fell within a confidence range of 0.50–0.80 with relatively large pixel areas, indicating optimal detection when the flame was clearly visible. At 150 cm and especially 200 cm, pixel areas decreased substantially, accompanied by lower and more dispersed confidence values, reflecting reduced detection accuracy for smaller flames. Despite a few outliers at close range caused by flame fluctuations or lighting variations, the overall trend remained positive, with larger pixel areas corresponding to higher confidence. These results confirmed that detection performance was most stable at 50–100 cm and degraded at longer distances due to object scaling and loss of visual detail.

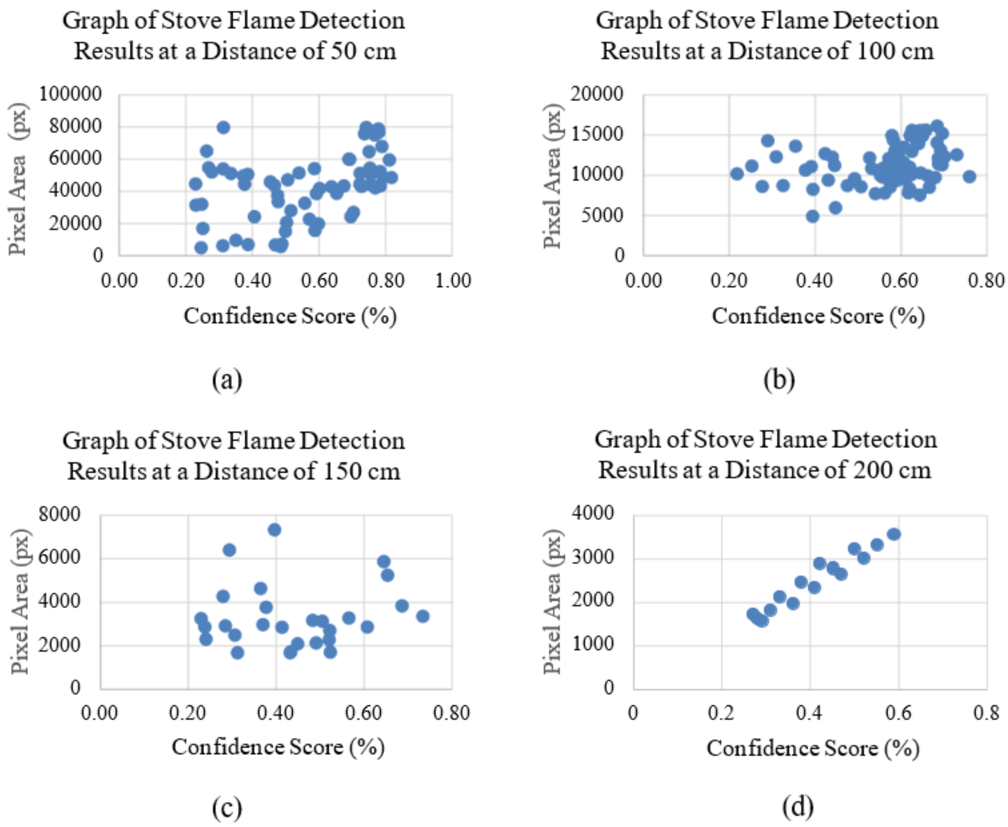


Figure 5. Relationship between confidence value and the size of the pixel area of stove flame detection (a) Distance 50 cm (b) Distance 100 cm (c) Distance 150 cm (d) Distance 200 cm.

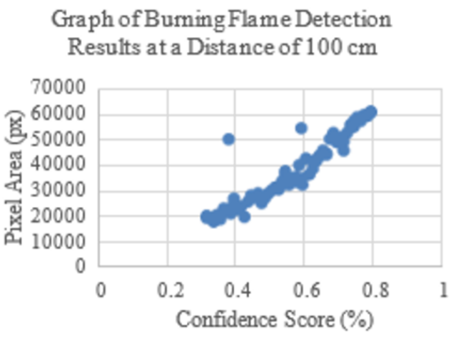
3.1.3. Burning fire.

Table 3 summarized the burning fire detection performance of IP Camera 1 at varying distances, reporting the average and standard deviation of confidence scores, bounding box pixel areas, and recall. The burning fire detection performance at various distances is presented in Table 3. At a distance of 100 cm, the system achieved an average confidence of 0.56 (SD = 0.13) with a bounding box area of 37,629 px (SD = 12,978 px), resulting in a recall of 58.9%. At 200 cm, the system showed an improved confidence of 0.72 (SD = 0.12) with a bounding box area of 48,932 px (SD = 12,370 px) and a recall of 78.94%. At the maximum tested distance of 300 cm, detection remained reliable, achieving a confidence of 0.71 (SD = 0.05) and a bounding box area of 44,805 px (SD = 7,268 px), with a perfect recall of 100%. The improved performance at 200 cm and 300 cm was attributed to increased flame growth, which resulted in a larger pixel area for the bounding box, leading to near-perfect recall values. These results indicated that the system's detection performance was primarily influenced by the apparent flame size and image clarity rather than camera distance alone. Reliable detection occurred when the flame occupied a sufficiently large pixel area, with optimal performance observed at 300 cm, which represented the maximum testing distance in the current indoor environment.

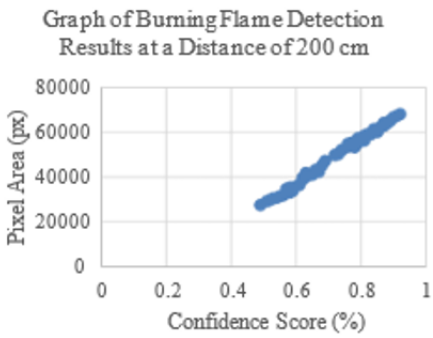
Table 3. IP CAMERA 1 burning fire detection test results.

Distance (cm)	No. of Sample	Confidence Score (%)		Pixel Area (px)		TP	FN	Recall (%)	Fire Class
		Avg	SD	Avg	SD				
100	73	0.56	0.13	37.629	12.978	43	30	58.9	Medium fire
200	57	0.72	0.12	48.932	12.370	45	12	78.94	Large fire
300	30	0.71	0.05	44.805	7268	30	0	100	Large fire

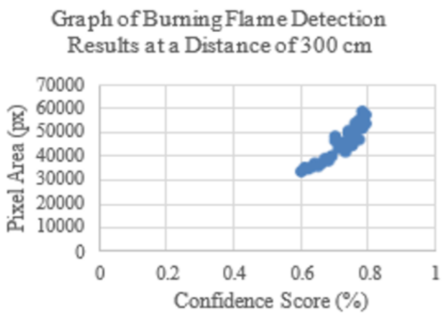
Based on the graphs at distances of 100 cm, 200 cm, and 300 cm, a positive correlation was observed between the confidence values and the pixel area of large fire detections (Figure 6). Higher confidence values corresponded to larger pixel areas of the detected fire. At 100 cm, the data showed a fairly wide variation in pixel area, whereas at 200 cm the distribution was more stable and formed a linear pattern. At 300 cm, the data points appeared more concentrated, with a narrower range of pixel areas.



(a)



(b)



(c)

Figure 6. Relationship between confidence value and the size of the pixel area of burning flame detection (a) Distance 100 cm (b) Distance 200 cm (c) Distance 300 cm.

3.2. Discussion of detection performance.

The experimental results demonstrated that fire detection performance was strongly influenced by the apparent visual size of the flame, as represented by the bounding box pixel area and confidence score. Larger flames consistently produced higher confidence values and more stable recall, confirming that sufficient visual information was essential for reliable feature extraction in YOLO-based fire detection systems [19, 20]. For candle flames, detection performance decreased significantly at distances beyond 100 cm due to limited pixel area and reduced flame visibility. At

50 cm, the average pixel area reached 3,252 px with a recall of 90.24%, while at 100 cm, the pixel area decreased to 1,090 px with reduced confidence (0.27). Although recall remained at 100%, no detections were recorded at 150 cm, indicating that flames with pixel areas below approximately 1,500 px could no longer be reliably detected. This phenomenon occurred because small objects provided fewer discriminative visual features for convolutional neural networks, resulting in reduced detection reliability [21, 24].

In contrast, stove flames and burning fires exhibited improved performance when larger flame regions were present. For stove flames, optimal performance was achieved at 50–100 cm, where pixel areas ranged from 11,144 to 42,525 px and recall exceeded 93%. However, when pixel areas decreased below 3,500 px at distances of 150–200 cm, recall dropped sharply to below 11%. Similarly, burning fires at 200–300 cm produced large pixel areas above 44,000 px, resulting in confidence values above 0.70 and recall rates of 78.94% to 100%. These results confirmed that flame growth significantly enhanced detection reliability by increasing spatial feature availability [18, 22]. The positive correlation between pixel area and confidence score observed in this study supported the theoretical relationship between object scale and classification reliability in deep learning-based detection systems. As the number of effective pixels representing the target increased, the signal-to-noise ratio of visual features improved, thereby enhancing detection stability and reducing false-negative occurrences [9, 23].

However, detection performance was also influenced by hardware and environmental factors. The limited processing capability of the Orange Pi 4A and variations in indoor lighting conditions affected frame processing speed and feature consistency, particularly for small flames and low-contrast backgrounds. These constraints contributed to unstable confidence values and delayed detections under challenging visual conditions. Similar limitations have been reported in embedded vision systems deployed for real-time monitoring applications [13, 15]. Compared with existing embedded fire detection systems, the proposed approach demonstrated competitive performance for medium- and large-scale fires while maintaining low cost and real-time operation. Nevertheless, sensitivity to small flames at longer distances remained a major limitation, consistent with findings in previous YOLO-based fire detection studies [11, 14]. Overall, the results indicated that reliable fire detection in indoor environments required sufficient visual resolution, appropriate camera placement, and adaptive threshold calibration. Future research should focus on multi-camera fusion, higher-resolution imaging, and lightweight model optimization to enhance small-flame detection and system scalability.

3.3. Multi-camera architecture analysis.

Several previous studies reported that multi-camera and multi-sensor architectures could improve fire detection coverage, reduce visual occlusion, and enhance system robustness in complex indoor environments [25–28]. By utilizing multiple viewpoints and complementary sensing modalities, such systems were able to provide more reliable spatial information for early fire detection. In the proposed system, the overall architecture was designed to support multi-camera integration using a single Orange Pi 4A as the central processing unit. This design enabled multiple IP cameras to be connected and managed simultaneously, allowing scalable deployment in larger monitoring areas. Similar centralized processing approaches have been shown to be effective for video-based fire detection systems in previous studies [26, 27].

However, in the experimental evaluation conducted in this study, only a single IP camera was utilized. This configuration was considered sufficient for the controlled 3 × 3 m indoor test environment, where adequate visual coverage and reliable detection performance could be achieved, particularly for medium- and large-scale fire sources. The use of a single-camera setup also facilitated more stable statistical evaluation and performance analysis, as recommended in standard detection assessment studies [24]. The single-camera configuration adopted during testing reduced hardware complexity and ensured controlled experimental conditions. Nevertheless, this setup inherently limited spatial coverage and increased vulnerability to visual occlusion, which has been identified as a major challenge in video-based fire detection systems [27, 28]. For larger industrial rooms or multi-zone facilities, the proposed system could be extended by deploying multiple cameras connected to the same embedded processing unit. This multi-camera configuration was expected to enhance detection robustness, spatial coverage, and reliability, consistent with multi-view and sensor-fusion-based fire detection approaches reported in the literature [26, 28]. Therefore, while the current experimental results demonstrated the effectiveness of the system in small- to medium-scale indoor environments, future work will focus on validating the proposed multi-camera architecture in large-scale industrial monitoring scenarios, with particular emphasis on optimizing computational efficiency and inter-camera data fusion strategies [24, 26].

4. Conclusions

This study demonstrated that a YOLOv11-based fire detection system implemented on the Orange Pi 4A and integrated with Internet of Things (IoT) monitoring was capable of performing real-time indoor fire detection with good accuracy, particularly for medium- and large-scale fires. The experimental results indicated that detection performance was more strongly influenced by the apparent visual size of the flame, represented by the bounding box pixel area, than by camera distance alone. Stable detection of candle flames was achieved up to 100 cm, with recall values of 90.24%–100%, while stove flames showed optimal performance at 50–100 cm, with recall exceeding 93%. For burning fires, high detection reliability was maintained up to 300 cm, with confidence values above 0.70 and recall ranging from 78.94% to 100%. Furthermore, continuous flame growth was observed to cause a gradual increase in the detected pixel area over time. In a monitoring system with 30–60 second intervals, this increase in visual size led to higher confidence values and elevated hazard classification levels. When predefined thresholds were exceeded, the system automatically activated an alarm, enabling early warning based on both flame presence and temporal intensity progression. Overall, the proposed system demonstrated strong feasibility for early fire warning applications in indoor industrial environments by providing a low-cost embedded solution integrated with IoT and automated data logging. However, the system remained limited in detecting small flames and was dependent on camera resolution, lighting conditions, and embedded processing capability. Future work will focus on improving small-flame detection through higher-resolution imaging, multi-camera fusion, adaptive threshold calibration, and lightweight model optimization to enhance robustness, scalability, and generalization.

Acknowledgments

The author gratefully acknowledged the Electrical Engineering Department of Universitas Multi Data Palembang for providing laboratory facilities and technical support during this research. The author also thanked the academic supervisors and laboratory staff for their valuable guidance and assistance throughout the study. Appreciation was further extended to the industrial facility where the experiments were conducted for granting permission and providing operational support during system implementation.

Author Contribution

Safeti Intan Pratiwi contributed to the conceptualization, methodology design, experimental implementation, data collection, analysis, and manuscript writing. Eka Puji Widiyanto contributed to supervision, validation of experimental procedures, data interpretation, and critical review of the manuscript. All authors have read and approved the final version of the manuscript.

Competing Interest

The author declares that there are no competing interests related to this research.

References

[1] Gujjar, H.S. (2025). Real-Time Video-Based Fire Detection Using Deep Learning Techniques: A Study of YOLO and CNN Architectures. *International Journal of Scientific Research in Multidisciplinary Technology*, *4*, 1–2. https://doi.org/10.38124/ijsrmt.v4i7.650.

[2] Naik, S.P.; et al. (2023). Fire Detection with Image Processing. *International Journal for Research in Applied Science & Engineering Technology*, *2023*. https://doi.org/10.22214/ijraset.2023.52073.

[3] Vision-based Detection Algorithm for Monitoring Dynamic Change of Fire Progression. (accessed on 1 December 2025) Available online: https://link.springer.com/article/10.1186.

[4] Widharma, I.G.S.; et al. (2022). Deteksi Api Kebakaran Berbasis Computer Vision dengan Algoritma YOLO. *JAMETECH*, *3*, 53–58. https://doi.org/10.31940/jametech.v3i2.53-58.

[5] Fadlol, M.T.; et al. (2024). Penerapan Deteksi Titik Api pada Area Graving Dock Menggunakan YOLO dan Grad-CAM. *ELKOLIND*, *12*, 1. https://doi.org/10.33795/elkolind.v12i1.7253.

[6] Adi, M.A.A.; et al. (2024). Implementasi Sistem Deteksi Titik Api pada Area Graving Dock Menggunakan YOLOv5. *ELKOLIND*, *11*, 2. https://doi.org/10.33795/elkolind.v11i2.5233.

[7] Maulana, F.; et al. (2024). Sistem Smart Home untuk Deteksi Potensi Kebakaran Berbasis IoT. *Jurnal Penelitian Ilmu Teknik*, *10*, 1. https://doi.org/10.30591/jpit.v10i1.8176.

[8] Author, T.X. (2024). Visual Fire Detection Using Deep Learning: A Survey. *Neurocomputing*, *596*, 127975. https://doi.org/10.1016/j.neucom.2024.127975.

[9] Author, A. (2021). Real-Time Video Fire/Smoke Detection Based on CNN in Antifire Surveillance Systems. *Journal of Real-Time Image Processing*, *2021*. https://link.springer.com/article/10.1007.

[10] Author, B. (2024). Efficient Forest Fire Detection Based on an Improved YOLO Model. *Visual Intelligence*, *2024*. https://link.springer.com/article/10.1007.

[11] Author, C. (2025). FB-YOLOv8s: A Fire Detection Algorithm Based on YOLOv8s. *Cognitive Robotics*, *2025*. https://doi.org/10.1016/j.cogr.2025.06.002.

[12] Rajalakshmi, P.; Rohini, P. (2025). Integrating YOLO for Real-Time Fire Detection in Smart Surveillance Systems. *International Journal of Scientific Research in Computer Science & Information Technology*, *11,* 848-853. https://doi.org/10.32628/CSEIT25113347.

[13] Zhang, D. (2024). A YOLO-Based Approach for Fire and Smoke Detection in IoT Surveillance Systems. *International Journal of Advanced Computer Science and Applications*, *15*, 1.

https://dx.doi.org/10.14569/IJACSA.2024.0150109.
[14] Khemnar, K.C.; et al. (2025). Fire Detection Using Deep Learning. *International Journal of Scientific Research in Science, Engineering and Technology*, *2025*. https://doi.org/10.32628/IJSRSET2513860.
[15] Wicaksono, P. (2024). Deep Learning Wildfire Detection to Increase Fire Safety with YOLOv8. *International Journal of Intelligent Systems and Applications in Engineering*, *2024*. https://ijisae.org/index.php/IJISAE/article/view/6190/4981.
[16] Hassan, J.K.; Audu, A. (2022). A Review on Vision-Based Fire Detection Systems: Advantages over Conventional Sensors. *Journal of Fire Safety and Technology*, *12*, 45–56. https://doi.org/10.5772/58821.
[17] Sharma, P.; et al. (2021). Comparative Study of Fire Detection Methods: Sensor-Based vs. Computer Vision-Based Approaches. *International Journal of Intelligent Engineering and Systems*, *14*, 112–121.
[18] Zhang, L.; Yang, M. (2023). Real-Time Indoor Fire Detection Using Image Processing and IoT Integration. *Sensors*, *23*, 521. https://doi.org/10.33093/ijoras.2021.3.4.
[19] Elhanashi, A.; Essahraui, S.; Dini, P.; Saponara, S. (2025). Early Fire and Smoke Detection Using Deep Learning: A Comprehensive Review of Models, Datasets, and Challenges. *Applied Science*, *15*, 10255. https://doi.org/10.3390/app151810255.
[20] Moumgiakmas, S.S.; Samatas, G.G.; Papakostas, G.A. (2021). Computer Vision for Fire Detection on UAVs—From Software to Hardware. *Future Internet*, *13*, 200. https://doi.org/10.3390/fi13080200.
[21] Bhatt, A.; Patel, V. (2022). IoT-Enabled Vision-Based Fire Detection Systems for Industrial Safety. *Journal of Industrial Information Integration*, *27*, 100340.
[22] Redmon, J.; Farhadi, A. (2017). YOLO9000: Better, Faster, Stronger. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, *2017*. https://doi.org/10.1109/CVPR.2017.690.
[23] Shahriar, S.M.; et al. (2025). Indoor Fire and Smoke Detection Based on Optimized YOLOv5. *Journal of Sensors*, *2025*. https://pmc.ncbi.nlm.nih.gov/articles/PMC12040180/.
[24] Fawcett, T. (2006). An Introduction to ROC Analysis. *Pattern Recognition Letters*, *27*, 861–874. https://doi.org/10.1016/j.patrec.2005.10.010.
[25] Yuan, F.; Zhang, Y.; Xia, Z.; Fang, B. (2012). Fire Detection Using Multi-View Cameras. *Pattern Recognition Letters*, *33*, 1569–1577. https://doi.org/10.1016/j.patrec.2012.05.009.
[26] Muhammad, K.; Ahmad, J.; Mehmood, I.; Rho, S.; Baik, S.W. (2018). Convolutional Neural Networks Based Fire Detection in Surveillance Videos. *IEEE Access*, *6*, 18174–18183. https://doi.org/10.1109/ACCESS.2018.2812835.
[27] Çelik, T.; Demirel, H.; Özkaramanlı, H.; Uyguroğlu, M. (2007). Fire Detection Using Statistical Color Model in Video Sequences. *Journal of Visual Communication and Image Representation*, *18*, 176–185. https://doi.org/10.1016/j.jvcir.2006.12.003.
[28] Verstockt, S.; Lambert, P.; Van de Walle, R. (2010). Detection of Fire in Video Sequences Using Multi-Sensor Fusion. *Optical Engineering*, *49*, 8. https://doi.org/10.1117/1.3463475.