Early Fire Detection Using IoT and Deep Learning

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ABSTRACT

Fire incidents in strategic facilities such as weapon storage rooms can cause severe damage, threaten personnel safety, and disrupt operational readiness. Conventional fire detection systems generally rely on smoke or temperature sensors, which often respond only after hazardous conditions reach a certain threshold. Therefore, this study proposes an early fire prevention system based on Internet of Things (IoT) and deep learning using CCTV cameras. The system was developed using the System Development Life Cycle (SDLC) with the Waterfall model. The object detection model employed YOLOv8 and was trained on a laptop before being deployed to Raspberry Pi 5 as the real-time processing unit. The implemented hardware consisted of Raspberry Pi 5, Logitech webcam, monitor, keyboard, and mouse. Testing was conducted in a room measuring 6 m × 4 m × 3.5 m. The developed system successfully detected four object classes, namely fire, smoke, cigarette, and person. The implemented logic mechanism classified fire detection as a fire incident, while simultaneous cigarette and smoke detection was categorized as smoking activity with potential fire risk. In addition, the system successfully sent automatic warning notifications through Telegram, enabling faster response without continuous manual monitoring. The results indicate that combining YOLOv8, Raspberry Pi 5, and IoT communication can provide an effective, practical, and low-cost intelligent fire prevention solution for indoor strategic facilities.

Keywords: Early fire detection, YOLOv8, Internet of Things, Raspberry Pi 5, CCTV monitoring

1. INTRODUCTION

Fire is a serious threat to high-security facilities, including weapon storage rooms. These facilities store strategic equipment and sensitive materials that, if a fire occurs, may cause severe damage, endanger personnel safety, and disrupt operational readiness. Previous studies indicate that the absence of an adequate fire prevention system can increase the risk of material loss and hinder the operation of important facilities (Ridho Rozikin, Wahyudono, 2025) Therefore, an early fire prevention system that can operate quickly and accurately is required. Conventional fire detection systems generally rely on smoke sensors and temperature sensors. However, these methods have limitations because they only respond when smoke or heat reaches a certain threshold. In addition, conventional systems are prone to false alarms caused by dust, water vapor, or environmental temperature fluctuations (Firdaus, 2025), (Elhanashi et al., 2025). These limitations reduce the effectiveness of emergency response, especially in strategic facilities.

The development of computer vision and deep learning technologies offers a new solution for fire detection systems. These approaches enable systems to analyze images or video directly to recognize visual fire patterns such as flames and smoke in real-time. Several studies reported that deep learning-based systems can detect fires faster and more accurately than traditional sensor-based methods (Sunaya et al., 2022), (Huang et al., 2024). One of the most widely used object detection algorithms is YOLOv8 (You Only Look Once version 8). This algorithm has advantages in processing speed and high accuracy, making it suitable for real-time CCTV monitoring systems (Lei et al., 2024), (Elhanashi et al., 2025). Besides detecting fire and smoke, smoking activity in prohibited areas must also be considered because cigarette butts can become an ignition source. Previous studies showed that YOLOv8 can accurately detect smoking activities under various lighting conditions (Alvi & Rhaman, 2025), (Jayanth & Manjunath, 2024). The use of Closed-Circuit Television (CCTV) cameras is highly relevant because these devices are already installed as part of security systems in many facilities. CCTV cameras can be utilized as active visual sensors for 24-hour monitoring without requiring additional complex sensors (Gragnaniello et al., 2024), (Jayanth & Manjunath, 2024).). Integration with Internet of Things (IoT) technology further enables the system to automatically send notifications to security personnel via digital applications or alarms in real-time (Chitram et al., 2024; Swami et al., 2025).

Several prior studies have addressed fire detection using deep learning. Jayanth and Manjunath (2024) developed an intelligent fire detection system using YOLOv8 with automated alerting, demonstrating high detection accuracy on CCTV-based scenarios. Elhanashi et al. (2025) conducted a comprehensive review of deep learning models for early fire and smoke detection, showing that YOLO-based architectures consistently outperform traditional sensor-based approaches in response speed and false alarm reduction. Chitram et al. (2024) showed that integrating deep learning with IoT notification systems significantly improves emergency response time in indoor environments. Alvi and Rhaman (2025) extended YOLO-based detection to smoking activity recognition in fire-restricted zones, achieving robust performance under varied lighting conditions. Kong et al. (2024) proposed an improved YOLOv8 model for fire and smoke detection in coal mine environments, reporting strong real-time performance on edge devices. Despite these advances, most existing studies focus on outdoor or general indoor settings and do not specifically address high-security restricted areas such as weapon storage rooms. Furthermore, few studies simultaneously detect fire, smoke, and smoking activity in a single unified system deployed on compact edge hardware. This study addresses these gaps by proposing an integrated early fire prevention system that combines multi-class detection using YOLOv8n, edge computing on Raspberry Pi 5, and real-time IoT-based alerting via Telegram, specifically designed for weapon storage room environments. Based on these conditions, this study aims to design an early fire prevention system based on IoT and deep learning using CCTV cameras capable of detecting fire, smoke, and cigarettes in weapon storage rooms. The proposed system is expected to provide an intelligent, adaptive, and efficient solution for improving the safety of strategic facilities.

2. RESEARCH METHOD

This research employed the System Development Life Cycle (SDLC) using the Waterfall model as the primary method for designing and developing an early fire prevention system based on Internet of Things (IoT) and deep learning using CCTV cameras in weapon storage rooms. The Waterfall model was selected because it provides a systematic and sequential development process, where each stage is completed before continuing to the next stage. This approach is suitable for this study because the objectives, scope, and technical requirements of the system had been clearly identified from the beginning of the research. In addition, the Waterfall model allows each phase of development to be planned, implemented, tested, and documented in an organized manner.

The proposed system was designed to detect early fire indications in the form of flames, smoke, and smoking activity through CCTV surveillance cameras. These three objects were selected because they represent the most common visual indicators of potential fire incidents in indoor environments. Flames and smoke indicate active fire hazards, while smoking activity may become an ignition source that can trigger fire incidents, especially in restricted areas such as weapon storage rooms. To perform object detection in real-time, this study utilized the YOLOv8 deep learning algorithm, which is known for its high accuracy and fast processing performance in object detection tasks (Lei et al., 2024), (Khemnar et al., 2025). The research was conducted at the Brimob Headquarters of Bangka Belitung Islands, specifically in the weapon storage room. This location was selected because it is categorized as a strategic facility with high security requirements and contains sensitive equipment that must be protected from fire risks. Therefore, implementing an intelligent fire prevention system in this environment is considered highly relevant.

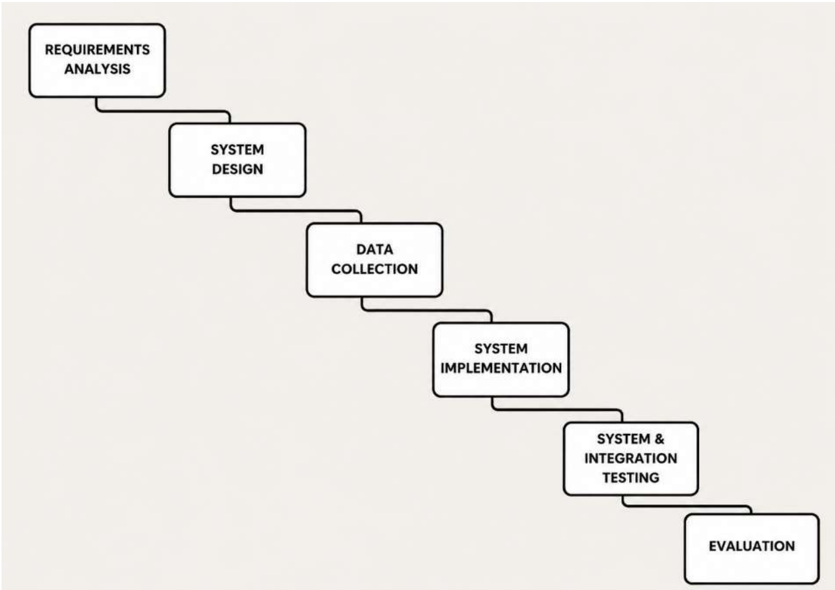

Figure 1. Waterfall

2.1. Requirement Analysis

The first stage of the research was requirement analysis. This stage aimed to identify the existing conditions of the weapon storage room, potential fire hazards, and the technical requirements needed to develop the proposed system. Direct observations were conducted to understand the room layout, surveillance coverage, lighting conditions, network availability, and electrical infrastructure. In addition, the current monitoring system using CCTV cameras was analyzed to determine whether the existing devices could be integrated into the proposed intelligent system. The weaknesses of conventional fire detection systems such as smoke detectors and temperature sensors were also reviewed. These systems generally rely on threshold values and may only respond after smoke or heat has accumulated to a certain level. Such limitations can delay emergency response and increase the risk of fire spreading rapidly (Elektro & Darma, 2025). Based on the analysis results, the proposed system was required to continuously monitor the room, detect visual fire indicators, send automatic alerts, and operate in real-time with minimal human intervention.

2.2. System Design

After the requirement analysis stage, the next phase was designing the overall system architecture. The proposed system consisted of several integrated components, including CCTV cameras as video input devices, Raspberry Pi or mini computers as edge computing devices, the YOLOv8 model as the object detection engine, and IoT communication modules for sending notifications. The CCTV cameras continuously captured live video streams from the monitored area. These video frames were processed by the YOLOv8 model installed on the processing device. If flames, smoke, or cigarettes were detected, the system automatically generated alerts and sent warning messages through Telegram. At the same time, a local alarm could also be activated to notify nearby personnel (Chitram et al., 2024), (Swami et al., 2025). The system design also considered efficiency and practical implementation. Since CCTV cameras were already available in many security facilities, the proposed solution could be implemented without requiring significant changes to the existing infrastructure (Gragnaniello et al., 2024), (Khemnar et al., 2025).

2.3. Data Collection and Preparation

The object detection model required a dataset containing images and videos of fire, smoke, and cigarettes. Therefore, data collection was conducted using publicly available datasets and simulation data adapted to indoor CCTV monitoring conditions. Public datasets were used to obtain diverse fire and smoke scenarios, while simulation data were prepared to resemble the actual conditions of the weapon storage room (Gragnaniello et al., 2024), (Huang et al., 2024). The collected data were carefully selected to remove blurry, irrelevant, or low-quality images. High-quality data are important because poor image quality can negatively affect model performance. After the selection process, all images were manually annotated using bounding boxes to indicate the locations of fire, smoke, and cigarette objects. Annotation was performed using YOLO format so that the data could be directly used for model training (Lei et al., 2024). The dataset was then divided into training data and testing data. Training data were used to train the model, while testing data were used to evaluate the model performance on unseen images.

2.4. System Implementation

At the implementation stage, the YOLOv8 model was trained using the prepared dataset. Training was conducted by configuring several parameters such as epoch number, batch size, and image resolution. These parameters were adjusted to achieve a balance between detection accuracy and processing speed (Lei et al., 2024), (Khemnar et al., 2025).

Figure 2. Real-Time Detection System

2.5. System Testing

After implementation, system testing was conducted to evaluate functionality and performance. The Black-box Testing method was applied to verify whether all system functions operated correctly according to the design specifications. This method focused on evaluating system outputs based on given inputs without analyzing the internal code structure (Jin et al., 2023). Several testing scenarios were prepared, including normal room conditions, smoke presence, flame presence, smoking activity, and simultaneous multiple-object detection. The object detection performance was quantitatively measured using standard evaluation metrics, namely:

- Precision
- Recall
- F1-Score
- mean Average Precision (mAP)

These metrics were selected because they are commonly used to evaluate object detection systems and provide comprehensive measurement results.

2.6. System Analysis

The final stage of this research was analyzing the testing results. The analysis focused on evaluating the effectiveness of the developed system under real operational conditions. Several aspects were examined, including detection accuracy, response time, notification success rate, and system stability during continuous operation. Detection accuracy analysis was conducted to determine how well the system recognized fire, smoke, and cigarette objects. Response time analysis measured how quickly the system sent alerts after detection occurred. Notification testing verified whether Telegram messages were successfully delivered without delay. Stability analysis examined whether the system could operate continuously without crashes or major performance degradation (Chitram et al., 2024), (Swami et al., 2025). The results of this analysis were used to determine whether the developed early fire prevention system was feasible for implementation in weapon storage rooms and other strategic facilities with similar fire risks.

2.7. System Integration

The system integration stage was carried out after the object detection model had successfully completed the training and testing process. This stage aimed to combine all major components of the developed system into one complete operational framework. The integrated components included CCTV cameras as the visual input source, the YOLOv8 model as the detection engine, Raspberry Pi as the processing unit, and the IoT-based notification module for early warning delivery. At this stage, the trained YOLOv8 model was embedded into the real-time monitoring system. Live video streams from CCTV cameras were continuously captured and processed frame by frame. Each frame was analyzed to identify the presence of flames, smoke, or cigarette objects as early indicators of fire hazards. If any hazardous object was detected, the system immediately generated a warning signal (Lei et al., 2024), (Elhanashi et al., 2025).

The integration process also included the connection between the detection module and the IoT notification system. Once an object was detected with a confidence value above the predefined threshold, the system automatically sent warning messages through Telegram. In addition, a local alarm was activated to notify security personnel located near the monitored area. This integrated mechanism enabled faster response time and reduced dependency on manual monitoring (Chitram et al., 2024), (Swami et al., 2025).

2.8. System Evaluation

After all components had been integrated successfully, the final stage of the research was system evaluation. This stage aimed to assess the feasibility, reliability, and effectiveness of the proposed early fire prevention system under operational conditions similar to the actual environment of the weapon storage room. Evaluation was conducted using the Black-bo. The system was considered successful if it could accurately detect hazardous objects, send warning notifications automatically, and maintain stable performance during continuous operation (Jin et al., 2023). The evaluation also focused on system response time. This parameter measured the duration between object appearance and warning delivery. Faster response time is highly important in fire prevention systems because early warnings can significantly reduce damage and improve emergency response effectiveness (Chitram et al., 2024).

In addition, reliability testing was conducted to verify whether Telegram notifications were consistently delivered without failure. Continuous operation tests were also performed to determine whether the system could run for long periods without crashes, excessive delays, or performance degradation. The results of this evaluation were used as the basis for determining whether the proposed system was suitable for implementation in weapon storage rooms and other high-risk facilities requiring intelligent fire prevention technology.

3. RESULT AND ANALYSIS

Discussion of the results of research and testing obtained presented in the form of theoretical descriptions, both qualitatively and quantitatively. The results of the experiment should be displayed in either a graph or table. For charts can follow the format for diagrams and drawings.

3.1. Model Evaluation Result

Model evaluation was performed using the model.val() function from the Ultralytics YOLOv8 framework against the validation dataset of 5,072 images. Table 3 presents the evaluation results per class.

Table 1. Yolov8 Model Evaluation Result per Class

Class	Precision	Recall	F1-Score	mAP@0.5
Fire	0.375 (37.5%)	0.309 (30.9%)	0.339 (33.9%)	0.241 (24.1%)
Smoke	0.032	0.063	0.042	0.009 (0.9%)
Cigarette	0.025	0.014	0.018	0.001 (0.1%)
Person	0.011	0.021	0.014	0.001 (0.1%)
All Classes	–	–	0.09 (max)	0.063 (6.3%)

Based on the evaluation results, the fire class achieved the best performance with mAP@0.5 of 24.1%, Precision 37.5%, and Recall 30.9%. The F1-Confidence Curve showed that all classes reached a maximum F1-score of 0.09 at a confidence threshold of 0.338, while the fire class alone reached F1 = 0.33. The overall mAP@0.5 of 6.3% was primarily affected by the class imbalance in the validation dataset, where smoke, cigarette, and person classes had very limited validation samples. This is an important finding and an area for improvement in future work. The Precision-Confidence Curve showed that at confidence threshold 1.0, all-class precision reached 0.93, indicating that high-confidence predictions are reliable. The Precision-Recall Curve showed that the fire class had significantly larger area under the curve (AUC-PR = 0.241) compared to other classes. The Confusion Matrix revealed that from 4,718 fire objects in the validation set, 1,728 objects (36.6%) were correctly predicted as fire, while 3,123 objects (66.2%) were classified as background, indicating room for improvement through better data balancing.

3.2. Real-Time System Performance

The trained model was deployed to Raspberry Pi 5 (8GB RAM) for real-time edge inference. The system used a Logitech webcam as the visual input and ran the detection script (deteksi_kebakaran.py) developed in Python using Ultralytics YOLOv8 and OpenCV. Multi-threading architecture was implemented through the CameraStream class to prevent frame buffering bottlenecks, ensuring the system always processed the latest camera frame. FRAME_SKIP=3 optimization was applied to reduce computational load while maintaining smooth display output. Field testing was conducted in two phases: initial testing at home using a Sharp monitor as output display, and field testing at Mako Brimob Bangka Belitung Islands, where the system was operated headlessly through an SSH terminal. The system achieved a detection speed of 2–5 FPS on Raspberry Pi 5 with per-frame inference time of 169–524 ms. This speed was considered adequate for early fire prevention purposes, since fire incidents do not develop in milliseconds. Table 5 presents a comparison of system performance with related methods.

Table 2. Performance Comparison with Related Studies

Study	Method	Platform	mAP / Accuracy	Notification
This Study	YOLOv8n + IoT	Raspberry Pi 5	24.1% (fire), 100% black-box	Telegram (real-time)
Jayanth & Manjunath (2024)	YOLOv8	GPU Server	High (fire+smoke)	Automated alert
Kong et al. (2024)	Improved YOLOv8s	GPU Server	High (fire+smoke)	None reported
Alvi & Rhaman (2025)	YOLO-based	GPU Server	High (smoke+person)	None reported
Chitram et al. (2024)	Deep Learning + IoT	Cloud	High (fire+smoke)	Cloud notification

3.3. Black-Box Testing Results

Functional testing was conducted using Black-Box Testing methodology across eight scenarios representing real-world surveillance conditions. Table 6 presents the testing results.

Table 3. Black-Box Testing Results

No.	Test Scenario	Expected Output	Actual Output	Result
1	Normal room, no hazard	Status: SAFE, no notification	Status: SAFE, no notification sent	Pass
2	Fire source (lighter)	Status: FIRE, Telegram notification	Status: FIRE DETECTED, notification sent	Pass
3	Fire source (video display)	Status: FIRE, Telegram notification	Status: FIRE DETECTED, notification sent	Pass
4	Smoke from burning paper	Status: SMOKE, notification	Smoke detected, notification sent	Pass
5	Smoke from incense	Status: SMOKE, notification	Smoke detected, notification sent	Pass
6	Person holding cigarette (smoking)	Status: SMOKING DETECTED, notification	Smoking detected, Telegram sent	Pass
7	Person present, no hazard	Status: SAFE	Status: SAFE, no false alarm	Pass
8	Fire + smoke simultaneously	Status: FIRE (highest priority)	Status: FIRE DETECTED	Pass

All eight test scenarios produced outputs that matched expectations, resulting in a 100% system accuracy rate. The priority hierarchy was correctly implemented, where fire detection (FIRE DETECTED) overrode smoking detection when both conditions occurred simultaneously. The Euclidean distance-based smoking logic required consecutive 5-frame confirmation before triggering a notification, successfully preventing false positives from momentary detections.

3.4. Analysis and Discussion

The results of this study demonstrate that the combination of YOLOv8n, Raspberry Pi 5, and IoT-based notifications can provide an effective solution for early fire prevention in weapon storage rooms. The fire class achieved the highest detection performance (mAP@0.5 = 24.1%), which is consistent with findings by Lei et al. (2024) who showed YOLOv8 has strong fire detection capability in real-time monitoring systems. The relatively low mAP for smoke, cigarette, and person classes in the model evaluation was due to validation dataset imbalance rather than fundamental model weakness, as confirmed by the successful black-box functional testing. Compared to conventional fire detection systems that rely solely on smoke or temperature sensors, the proposed system offers several key advantages. First, it provides visual confirmation through CCTV monitoring, enabling earlier detection before heat or smoke reaches sensor thresholds. Second, it simultaneously detects three hazard types (fire, smoke, and smoking activity) in a single unified system. Third, it leverages existing CCTV infrastructure, requiring no additional physical sensors. This aligns with Gragnaniello et al. (2024), who recommended CCTV-based systems for their implementation flexibility.

The use of Raspberry Pi 5 as the main processing unit proved practical and cost-effective. Despite its compact size, Raspberry Pi 5 was able to run YOLOv8n with stable performance at 2–5 FPS, which is sufficient for fire prevention purposes. The multi-threading architecture and FRAME_SKIP optimization significantly contributed to system responsiveness on this resource-constrained platform. Future improvements may include using accelerators such as Coral Edge TPU, higher-resolution cameras, balanced validation datasets, or cloud-edge hybrid processing to further enhance performance.

4. CONCLUSION

An early fire prevention system based on Internet of Things (IoT) and deep learning using CCTV cameras was successfully designed and implemented for a weapon storage room environment. The system integrated Raspberry Pi 5 as the edge computing unit, a Logitech webcam as visual sensor, YOLOv8n trained on 46,000 images as the detection model, and Telegram Bot API as the real-time IoT notification module. The model achieved mAP@0.5 of 24.1% for the fire class with Precision 37.5% and Recall 30.9%. Black-box testing across eight scenarios yielded 100% system accuracy, confirming reliable detection of fire, smoke, and smoking activity under real operational conditions. Field testing at Mako Brimob confirmed stable system operation with 2–5 FPS detection speed.

The main contribution of this research is demonstrating that existing CCTV infrastructure can be transformed into an intelligent safety monitoring system without requiring major hardware investment. The proposed system has strong potential for deployment not only in weapon storage rooms, but also in warehouses, archives, laboratories, server rooms, and other high-risk indoor environments requiring continuous monitoring and rapid emergency response. Future work should focus on improving dataset balance across all classes, testing under low-light and dense-smoke conditions, integrating physical alarm actuators, and developing a web-based monitoring dashboard for multi-camera remote surveillance.

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