

# Design and Implementation of a Raspberry Pi-Based Automated Fire Extinguishing System Utilizing YOLOv11 and Multi-Sensor Fusion

## Abstract

Fire incidents remain a critical safety challenge, requiring rapid detection and efficient suppression to minimize risks to life and property. Conventional fire detection systems based solely on smoke or flame sensors often suffer from false alarms, delayed responses, and limited coverage. To address these issues, we propose a **multi-sensor, vision-guided fire extinguishing system** that integrates **YOLOv11n-based computer vision** with real-time actuation for precise fire suppression. The system is powered by a Raspberry Pi 5, connected to a Pi Camera v1.3, MQ-5 smoke sensor, and IR flame sensor for robust fire and smoke detection. A custom dataset comprising **32,603 labeled images** including **fire (class 0) and smoke (class 1)** instances, was used to train YOLOv11n, achieving reliable real-time detection. The model outputs bounding box coordinates of fire or smoke, which are dynamically mapped to servo motor movements for nozzle alignment. A 12 VDC double motor pump, controlled via L298N, regulates water flow through a brass nozzle, ensuring water is directed precisely at the fire source instead of indiscriminate spraying. Experimental results demonstrate that the system achieves high detection accuracy for both fire and smoke, reduces false positives through multi-sensor fusion, and optimizes water usage via targeted extinguishing. This research presents a lightweight, cost-effective, and scalable solution with potential applications in **smart homes, industrial facilities, and autonomous safety systems**.

## 1. Introduction

Fire incidents represent a persistent threat to public safety and economic stability across global communities. Annually, these events result in substantial casualties, injuries, and considerable property damage. For instance, in 2021, the United States alone recorded approximately 1.35 million fires, leading to 3,800 fatalities and an economic loss exceeding \$15.9 billion [1]. Residential fires account for a significant portion of these incidents, with causes ranging from cooking mishaps to electrical malfunctions [2]. The rapid proliferation of fire underscores the necessity of early and accurate detection, as well as swift, automated intervention, to mitigate widespread destruction and protect lives[2].

Traditional fire detection systems predominantly rely on sensor-based methodologies, employing smoke, heat, and gas sensors [1][3]. While fundamental, these sensors possess inherent limitations. They often require a substantial accumulation of smoke or heat to trigger an alarm, delaying early detection [4]. Furthermore, their operational principles frequently lead to high rates of false alarms, for example, from cooking fumes or dust, and they generally cannot ascertain the precise location of a fire source [1]. Such systems also demand regular maintenance and component replacement, incurring additional costs [1]. Automated suppression systems, such as sprinklers, typically activate broadly, leading to significant water damage even for localized fires

[5] [6]. These constraints highlight a clear need for more sophisticated, responsive, and targeted fire management solutions.

This research presents an autonomous smart fire extinguishing system designed to overcome the limitations of existing solutions. The core innovation lies in the integration of real-time fire detection using a YOLOv11-based computer vision algorithm with a multi-sensor fusion approach and an automated, precision-targeting nozzle system. The system employs a for visual input, processing live feeds through a finely tuned YOLOv11n model to identify and localize fires with bounding box coordinates. Complementary data from MQ-5 smoke and IR flame sensors enhance detection reliability and minimize false positives. Upon positive identification, a Raspberry Pi 5 controller dynamically maps the fire's coordinates to control a servo motor, directing a brass nozzle for targeted water application. This integrated approach offers superior early detection, precise fire source localization, and efficient suppression, thus reducing both fire damage and the collateral impact of extinguishing efforts. The project's contributions extend to the practical implementation of a hardware prototype and the development of robust training protocols for the vision model, demonstrating a tangible advancement in autonomous fire safety technology.

## 2. Related Work

Fire detection and suppression have been widely explored using different approaches, ranging from traditional sensor-based systems to modern deep learning and computer vision techniques. Early approaches primarily focused on image-processing pipelines, where handcrafted features such as color, shape, and motion were analyzed to distinguish fire pixels from the background. For instance, Mondal et al. [5] proposed a multi-layered filtering method combining motion detection, histogram analysis, and variance analysis for fire identification in videos. Similarly, Sharma et al. [6] integrated IoT and RGB/YCbCr color models for urban fire detection, highlighting the potential of sensor-image hybrid systems.

Deep learning-based methods have significantly advanced fire detection performance. Dua et al. [7] employed pre-trained CNN architectures such as VGG and MobileNet to detect fire from image datasets, reporting improved accuracy compared to classical methods. Saponara et al. [8] further demonstrated the utility of YOLOv2 for real-time fire and smoke detection in surveillance systems, validating their results on a Kaggle dataset. Chetoui and Akhloufi[9] explored fine-tuned YOLOv7 and YOLOv8 models for fire and smoke detection, achieving high precision (95.4%) and strong recall (84.8%) on a dataset of 11,667 RGB images.

Recent studies have increasingly focused on advanced YOLO architectures. Ahn et al. [15] applied YOLOv5 for building fire detection using CCTV footage, while Yun He et al. [1] introduced a dual-channel bottleneck YOLO variant (DCGC-YOLO) to improve fire detection robustness. Srinivasan et al. [10] also demonstrated the potential of YOLOv8 in early fire detection, reporting improvements in false alarm reduction and reaction times.

Several works have investigated fire suppression in addition to detection. Khan et al. [11] presented a smart IoT-based fire detection and extinguisher recommendation system, integrating thermal and RGB cameras with SSD-Inception-V2. Dhiman et al. [12] developed a firefighting robot combining YOLOv5 with deep learning-based navigation, enabling both detection and suppression capabilities. Alqourabah et al. [13] also proposed an IoT-driven system that integrates flame, temperature, and gas sensors with automatic sprinklers for real-time fire mitigation.

Other research emphasizes specialized scenarios such as indoor fire detection [14] stereo camera-based fire size and power measurement [15] and forecasting of fire spread using computer vision

[16]. Fengju et al. [17] provided a comprehensive survey of intelligent vision-based fire detection, reviewing CNNs, Faster R-CNN, and SVM-based approaches.

From this body of work, it is evident that YOLO-based architectures have emerged as the most promising solution for real-time fire and smoke detection. However, challenges remain in minimizing false alarms due to light reflections and optimizing suppression mechanisms. Our work builds upon these advances by developing a **multi-sensor, YOLOv11n-based detection and targeted nozzle suppression system** addressing both detection reliability and efficient fire extinguishing.

### 3. System Architecture and Design

The proposed system is an **intelligent fire detection and suppression framework** that integrates computer vision, sensor fusion, and automated actuation for precise and efficient firefighting. The architecture combines real-time **YOLOv11n-based detection** with **multi-sensor inputs** to minimize false alarms and a **servo-controlled nozzle mechanism** to ensure targeted extinguishing of the fire source.

#### 3.1 Proposed Architecture

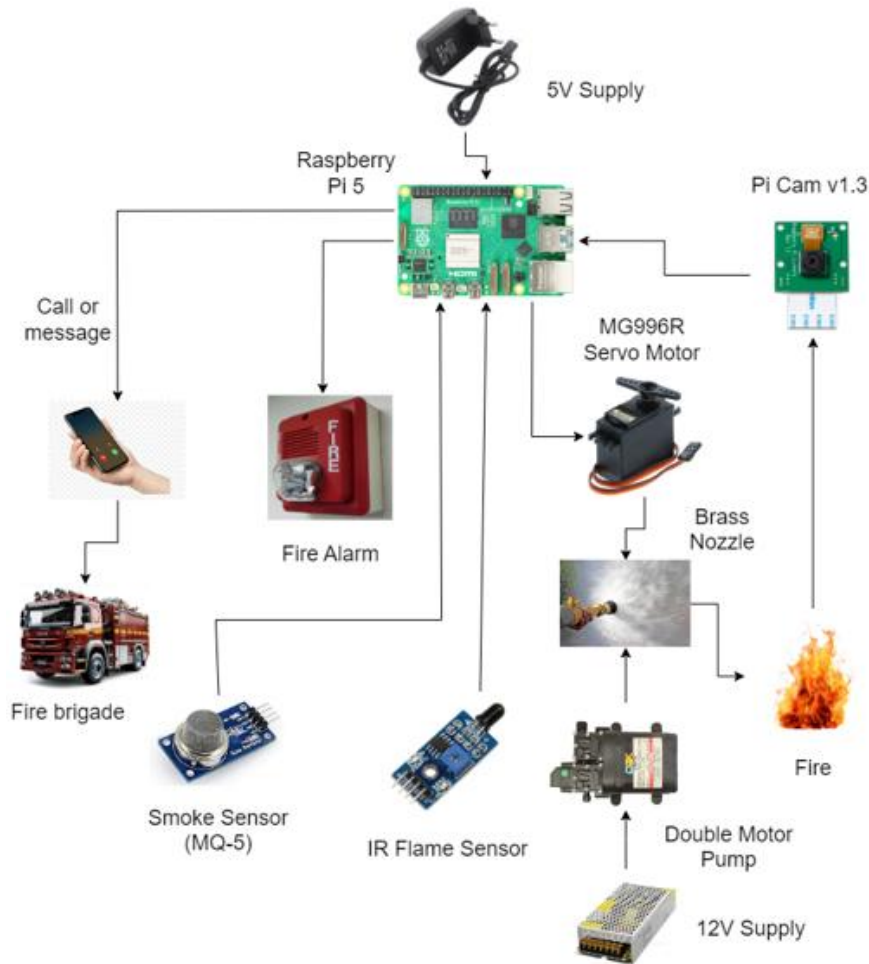


Figure 1. Proposed System Architecture for YOLOv11n-based Fire Detection and Suppression.

The system is structured around the **Raspberry Pi 5 (8 GB)** which serves as the central processing and control unit. A **Pi Camera v1.3** provides continuous video input, while an **MQ-5 smoke sensor** and an **IR flame sensor** act as secondary detection modalities. The detection subsystem employs a **custom-trained YOLOv11n model** which processes the camera feed to identify fire and smoke in real time and outputs bounding box coordinates of the detected regions. These coordinates are mapped into corresponding servo motor movements, enabling dynamic adjustment of a **brass nozzle** connected to a **12 VDC double motor pump**. Upon fire detection, the system activates a **buzzer** for alarm signaling, displays status information on a **16×2 LCD module** and triggers the pump via an **L298N motor driver** to spray water precisely onto the fire source. A **12 V/10 A power supply** drives the pump, while the Raspberry Pi and sensors operate on a **regulated 5 V supply**.

## 3.2 Hardware Implementation

The proposed fire extinguishing system was physically realized using a combination of low-cost yet efficient hardware components, carefully selected for real-time fire detection, decision-making, and suppression. Each hardware module contributes to the integrated operation of detection, targeting, and extinguishing subsystems.

### 3.2.1 Processing and Control Unit

The central processing unit of the system is the **Raspberry Pi 5 (8 GB RAM)** chosen for its enhanced computational capabilities compared to earlier versions. It manages the computer vision model, sensor data acquisition, and actuation commands in real time. The Raspberry Pi executes the YOLOv11n-based fire detection algorithm, processes bounding box coordinates, and issues control signals for nozzle targeting and pump activation.

### 3.2.2 Vision Hardware

A **Raspberry Pi Camera Board v1.3 (5 MP)** is employed to capture a live video feed for fire detection. The camera provides sufficient resolution and frame rate to support the lightweight YOLOv11n model without overloading the Raspberry Pi. Its field of view is aligned with the nozzle's motion range to enable effective coordinate mapping.

### 3.2.3 Actuation Components

The nozzle targeting mechanism is driven by **MG995 high-torque servo motors** responsible for adjusting the orientation of the brass nozzle along horizontal and vertical axes. These servos provide the required angular precision and torque for real-time alignment with detected fire coordinates.

Water is discharged using a **12 V DC double motor pump** controlled via an **L298N motor driver module**. The pump is powered by a **12 V/10 A supply** ensuring sufficient pressure for continuous water spraying through the brass nozzle.

### 3.2.4 Fire Detection Sensors

In addition to computer vision, hardware sensors provide redundant detection to reduce false positives and improve reliability. The system integrates:

- **MQ-5 Smoke Sensor** Detects early smoke signatures, enabling pre-flame detection and enhancing safety response.

- **IR 3-Wire Flame Sensor Module** Identifies infrared radiation emitted by flames, serving as an additional confirmation mechanism.

### 3.2.5 User Interface and Alerts

The system provides user feedback and alerts through a **16 × 2 LCD with I<sup>2</sup>C interface** which displays system status, sensor readings, and detection results. Additionally, a **5 V relay-controlled buzzer** acts as an audible alert, notifying nearby individuals of a fire event or system activation.

### 3.2.6 Fluid Storage and Discharge

A **dedicated water storage tank** supplies the extinguishing medium. The brass nozzle is designed to deliver a directed spray pattern, ensuring that water reaches the precise fire coordinates mapped by the targeting subsystem.

### 3.2.7 System Integration

All hardware modules are interconnected through the Raspberry Pi, which acts as the master controller. The camera and sensors provide input signals, which are processed by the YOLOv11n model and sensor fusion logic. Output signals are then sent to the servo motors, pump, and alert system, ensuring coordinated real-time fire detection and suppression.

## 3.3 Working Principle

The operational flow of the system is as follows:

1. **Fire and Smoke Detection** The Pi Camera continuously captures video, which is analyzed using YOLOv11n for fire and smoke detection. In parallel, the MQ-5 and IR flame sensor monitor environmental conditions for early signs of fire.
2. **Event Validation** Multi-sensor fusion ensures reliability by cross-verifying computer vision outputs with smoke and flame sensor readings, thereby reducing false positives caused by light reflections or camera noise.
3. **Alarm and Notification** Upon validated detection, the system activates a buzzer to provide an immediate local alert. Optionally, notifications can be extended to external communication modules for remote monitoring.
4. **Targeted Fire Suppression** YOLOv11n's bounding box coordinates are translated into angular movements of an **MG995 servo motor** aligning the brass nozzle toward the fire source. The double motor pump is then activated to deliver a controlled water spray, ensuring efficient extinguishing while minimizing water waste.
5. **System Feedback and Monitoring** The LCD module provides real-time system feedback, including detection status and operational state, allowing users to monitor system activity directly.

This integrated approach ensures that the system not only detects fire at an early stage but also responds **autonomously and precisely** thereby improving suppression efficiency compared to conventional systems that rely on manual intervention or indiscriminate water spraying.

## 4. Methodology

### 4.1 Detection Subsystem

The detection subsystem forms the core of the proposed fire extinguishing framework, enabling early and reliable identification of fire and smoke. It combines **deep learning–based computer vision** with **environmental sensor inputs** to ensure robust performance under diverse conditions.

#### 4.1.1 YOLOv11-Based Computer

At the heart of the detection module lies the **YOLOv11n object detection model** fine-tuned for a two-class task: **fire** and **smoke**. The model processes live video streams captured by the **Pi Camera v1.3** and detects fire or smoke in real time with high accuracy. Each detection is represented by a **bounding box and class confidence score** which not only confirms the presence of a hazard but also provides the **spatial coordinates** of the fire. These coordinates are later utilized for nozzle alignment and targeted suppression (Section 6).

The choice of YOLOv11n was motivated by its **lightweight architecture (2.59M parameters, 6.4 GFLOPs)** making it suitable for deployment on embedded platforms such as the Raspberry Pi 5. Despite its efficiency, the model achieves strong generalization across challenging scenarios, including reflections, partial occlusions, and varying illumination.

#### 4.1.2 Multi-Sensor Fusion

To improve detection accuracy, the system adopts a **multi-sensor fusion approach** where outputs from YOLOv11n, the MQ-5 smoke sensor, and the IR flame sensor are cross-validated. A fire event is only confirmed when the computer vision output is supported by sensor readings or when multiple sensors detect abnormal conditions simultaneously. This strategy significantly reduces **false positives** caused by light reflections, shadows, or environmental noise, while ensuring timely responses to both smoke and flame events.

Through this hybrid detection architecture, the subsystem achieves a balance between **early detection** (enabled by smoke sensors) and **precise localization** (enabled by computer vision), ensuring robust fire identification across a wide range of real-world scenarios.

### 4.2 Nozzle Targeting System

The nozzle targeting subsystem is responsible for translating the fire localization outputs from the detection module into precise mechanical actuation for fire suppression. By dynamically mapping image coordinates to real-world servo positions, the subsystem ensures that extinguishing agents are directed toward the exact location of the hazard.

#### 4.2.1 Dynamic Coordinate Mapping

The bounding box coordinates generated by the YOLOv11n detection model are first processed to determine the **centroid of the detected fire region**. This centroid is then mapped to a corresponding angle of rotation for the horizontal (X-axis) and vertical (Y-axis) servo motors. The mapping process employs a calibrated transformation function, aligning the **2D pixel coordinates** from the Pi Camera's field of view with the **servo's angular range**. This allows the system to dynamically adjust in real time as the fire spreads or relocates within the environment.

### 4.2.2 Servo Motor Alignment

The targeting mechanism is driven by two high-torque servo motors that control the orientation of the **brass nozzle** along both axes. Once the coordinates are translated into angular values, the servos rotate accordingly, ensuring that the nozzle is always aligned with the active fire region. This closed-loop alignment enables continuous tracking of fire movement, which is critical in fast-evolving scenarios where flames may shift due to airflow or material combustion.

### 4.2.3 Water Discharge Control

The extinguishing medium is delivered through a **brass nozzle** connected to an electric water pump. Upon confirmation of a fire event, the pump is activated, and water is discharged in a controlled jet directed at the fire's coordinates. The pump operates in **short bursts** governed by the system's logic, to optimize water usage while maintaining suppression effectiveness. The brass nozzle's design ensures a stable spray pattern, while the motor alignment guarantees targeted application, minimizing collateral water damage to surrounding areas.

### 4.2.4 Integration with Detection

The targeting subsystem operates in tandem with the detection module, receiving real-time updates from YOLOv11n outputs and sensor confirmations. In cases of multiple fire detections, the system prioritizes the **largest bounding box region** as the most critical target, suppressing it before moving to secondary regions. This ensures that the suppression strategy remains both **efficient and adaptive** addressing the most severe fire zones first.

## 4.3 Dataset and Model Training

### 4.3.1 Dataset Preparation

A custom dataset was curated to enable robust fire and smoke detection in real-world conditions. The dataset consists of **32,603 unique labeled images** containing instances of **fire (class 0)** and **smoke (class 1)**. Among these, **9,940 images** contain smoke, and the same subset also includes both fire and smoke, ensuring diverse representation of simultaneous hazards. In total, the dataset was split into **26,379 training images** and **4,394 validation images** each annotated with bounding boxes in YOLO format. The dataset captures a variety of fire scenarios, including lighter flames and challenging real-world conditions such as reflections, varying illumination, and different smoke densities. Publicly available datasets and additional images collected from online resources were combined to achieve sufficient scale and diversity [18][19].

### 4.3.2 Training Methodology

We fine-tuned a YOLOv11n model using the **Ultralytics framework v8.3.199** implemented in **PyTorch 2.2** with **Python 3.10.12**. The model was initialized with **COCO-pretrained weights**[20] and adapted for a two-class detection task (fire and smoke). YOLOv11n, with **2.59M parameters (6.4 GFLOPs)** was chosen for its lightweight architecture, making it suitable for deployment on embedded devices such as the Raspberry Pi 5.

Initial training runs were conducted on a **Dell laptop** (Intel Core i5, 8th Gen, CPU-only), where 10 epochs were completed to verify dataset quality, annotation consistency, and model stability. The main training was performed on an **NVIDIA Tesla V100-SXM2 GPU (32 GB)** with **Automatic Mixed Precision (AMP)** enabled to accelerate computation while reducing memory usage [21]. We used **8 workers** for efficient data loading and set a **deterministic seed (0)** to ensure reproducibility.

Training configuration was as follows:

- Input size:  $640 \times 640$
- Batch size: 64
- Epochs: 100
- Optimizer: SGD (lr = 0.01, momentum = 0.9, weight decay = 0.0005)
- Learning rate schedule: Automatic (Ultralytics adaptive selection)[22].

### 4.3.3 Data Augmentation

To enhance generalization, a variety of data augmentation techniques were applied, inspired by prior work on robust object detection [23][24]

- **Mosaic augmentation** (disabled during the last 10 epochs).
- **Random horizontal flipping** with probability  $p = 0.5$ .
- **HSV color-space augmentation** (hue = 0.015, saturation = 0.7, value = 0.4).
- **Random erasing** ( $p = 0.4$ ).
- **RandAugment** transformations.
- **Translation** (0.1) and **scaling** (0.5).

These augmentations ensured robustness across different lighting, orientations, and scene complexities.

### 4.3.4 Model Adaptation

From the **499 pretrained layers** 448 layers were transferred from the COCO-pretrained model. This allowed the YOLOv11n network to leverage previously learned general features while fine-tuning higher layers for fire- and smoke-specific detection. Such **transfer learning** has proven effective in object detection tasks with limited domain-specific data [25]. This strategy ensured efficient convergence and improved accuracy with fewer training epochs.

### 4.3.5 Model Availability

The complete **training code** and **dataset** are made publicly available on **Kaggle** and **GitHub** enabling reproducibility and further experimentation by the research community.

## 5. Results and Discussion

### 5.1 Model Performance Evaluation

### 5.2 System Performance and Discussion of Challenges

During the development and testing of the proposed fire detection and extinguishing system, several technical challenges were identified. To address these, targeted solutions were designed and implemented, resulting in improved system performance, reliability, and efficiency. The following subsections summarize the key challenges and corresponding solutions.



### False Positives and Multi-Sensor Fusion

One of the major issues encountered was the occurrence of false positives, where the vision-based YOLOv11n model misclassified reflections, shadows, or bright surfaces as fire. Such misdetections triggered unnecessary alarms and water discharge, compromising system reliability. To mitigate this, a **multi-sensor fusion strategy** was adopted by integrating the YOLOv11n model with an MQ-5 smoke sensor and an IR flame sensor. This redundancy required simultaneous confirmation across modalities, significantly reducing false alarms and improving the robustness of fire detection.

### Real-Time Processing Delays and Hardware Optimization

Initial implementation on lower-end embedded platforms introduced noticeable latency when processing high-resolution video streams. These delays negatively impacted the timeliness of suppression. To overcome this limitation, the system's computational backbone was upgraded to a **Raspberry Pi 5 (8 GB)**. The enhanced processing power enabled smooth execution of the detection pipeline and nozzle-targeting subsystem, thereby achieving real-time responsiveness during fire suppression tasks.

### Coordinate Mapping Accuracy and Calibration

Mapping the 2D bounding box coordinates of detected fires into servo motor angular positions posed calibration challenges. Even slight misalignments between the Pi Camera's field of view and the servo orientation resulted in off-target spraying. To address this, a **camera-servo calibration procedure** was developed, establishing a reliable mapping between detected fire centroids and nozzle orientation. This approach improved accuracy and ensured consistent targeting of suppression efforts.

### Water Resource Optimization and Smart Flow Regulation

Unregulated, continuous water pumping risked excessive consumption, particularly in cases involving small or partially obscured fires. To enhance efficiency, a **smart water flow regulation strategy** was introduced. Using the L298N motor driver and relay-based control, the pump operated in a pulse-regulated manner, adjusting flow intensity and duration according to the fire's estimated size and location. This adaptive approach minimized water wastage while maintaining suppression effectiveness.

## 6. Conclusion and Future Work

This work presented the design and implementation of a **YOLOv11n-based autonomous fire detection and extinguishing system** integrating computer vision, multi-sensor fusion, and dynamic nozzle targeting. The system successfully demonstrated the ability to detect both fire and smoke in real time, translate detection coordinates into servo motor actuation, and direct a brass nozzle for precise fire suppression. By leveraging the Raspberry Pi 5 as the central controller, along with supporting hardware such as smoke and flame sensors, water pumps, and a servo-based targeting mechanism, the proposed solution provides a cost-effective, scalable approach to autonomous fire safety systems.

The experimental results highlighted the system's strengths in **reliable fire detection, dynamic suppression targeting**, and **efficient resource utilization**. At the same time, challenges such as **false positives from reflections, latency in real-time processing**, and **coordinate calibration errors** were identified. These challenges were addressed through **multi-sensor fusion, hardware upgrades, camera-servo calibration techniques**, and **smart water regulation**, significantly improving overall system robustness.

## 7. Future Work

While the current implementation validates the feasibility of a low-cost autonomous fire extinguishing system, several directions remain for future development:

- **Thermal Imaging Integration:** Incorporating thermal cameras could enhance detection under low-light or smoke-obscured conditions, further reducing false positives.
- **Multi-Agent Collaboration:** Deploying multiple mobile or stationary units capable of communicating and coordinating could improve coverage in large or complex environments.
- **Edge AI Optimization:** Further model compression and quantization techniques could be explored to reduce computational load on embedded devices without sacrificing detection accuracy.
- **Alternative Suppression Agents:** Expanding beyond water-based suppression (e.g., foam or CO<sub>2</sub> cartridges) could make the system suitable for diverse fire classes, including electrical and chemical fires.
- **Field Deployment Studies:** Long-term testing in real-world environments (e.g., warehouses, data centers, residential settings) is essential to evaluate durability, reliability, and scalability under practical constraints.

In conclusion, the proposed system represents a **step toward autonomous, AI-driven fire safety solutions**, offering a foundation for future research and development in intelligent fire detection and suppression technologies.

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