

AI-Based Autonomous Fire Detection and Extinguishing Robot: Design, Implementation, and Performance Evaluation

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Abstract - Fire accidents continue to inflict devastating losses on human life, property, and the environment across residential, industrial, and public settings worldwide. Conventional fire suppression strategies remain fundamentally human-centric, exposing emergency personnel to extreme temperatures, dense toxic smoke, and the danger of structural collapse. To address these critical deficiencies, this paper presents the design, development, and performance evaluation of an artificial intelligence-based autonomous fire detection and extinguishing robot. The proposed system integrates the YOLOv5 real-time object detection framework deployed on a Raspberry Pi inference engine, an Arduino-based actuation platform, and a multi-modal sensor array comprising MQ-2 gas sensors, DHT22 temperature humidity sensors, and infrared flame detectors. Sensor fusion logic correlates visual classifications with environmental measurements to suppress false alarms caused by sunlight, reflections, cooking smoke, and non-hazardous steam. A four-wheel differential drive chassis equipped with an HCSR04 ultrasonic obstacle avoidance module enables autonomous navigation through cluttered indoor environments, while an onboard water-pump suppression system delivers targeted fire extinguishment. Experimental trials conducted under varied lighting, distance, and obstruction conditions confirm a detection accuracy exceeding 92%, with end-to-end response times below 8 seconds from initial flame identification to suppression activation. The results demonstrate that the integrated platform substantially outperforms conventional threshold-based detection methods and establishes a replicable framework for next-generation autonomous fire safety systems.

Key Words: Autonomous fire detection, YOLOv5, sensor fusion, ESP32/Raspberry Pi, Obstacle avoidance, fire extinguishing robot, deep learning, SLAM, Embedded systems, Computer vision

1.INTRODUCTION

Fire remains one of the most persistent and catastrophic threats to modern civilization. Residential dwellings, chemical warehouses, data centers, textile factories, and dense urban commercial complexes are equally vulnerable to rapid flame propagation, with seconds of delayed response often determining the difference between a contained incident and a large-scale disaster. According to global fire safety statistics, fire accidents account for millions of casualties annually and generate economic losses running into billions of dollars. The gravity of this problem is compounded by the fact that traditional fire suppression strategies—smoke alarms, sprinkler arrays, manual extinguishers, and human firefighting teams—are fundamentally reactive in nature. They rely on fixed installation points, passive sensing thresholds, and ultimately on human intervention at the point of maximum hazard.

Human firefighters entering burning structures face extreme thermal loads, reduced visibility caused by dense smoke, accumulation of toxic carbon monoxide and hydrogen cyanide, and the ever-present risk of structural failure. These physical constraints severely limit both the speed and effectiveness of manual suppression. The emergence of robotics and artificial intelligence as transformative engineering disciplines offers a

compelling path beyond these limitations. An autonomous robotic platform capable of

independently detecting, localizing, and extinguishing fires can serve as a first responder that does not tire, does not require protective gear delays, and can access spaces wholly inaccessible to human personnel. Over the past decade, the convergence of deep learning-based computer vision, miniaturized embedded computing, multi-modal sensor technology, and advanced autonomous navigation has made practical autonomous firefighting robots a realistic engineering ambition rather than a speculative concept.

Vision-based machine learning models, particularly convolutional neural network architectures such as the YOLO family of object detectors, enable real-time discrimination between genuine fire threats and visually similar false positive stimuli, including sunlight reflections, welding arcs, and non-hazardous steam columns. Simultaneously, autonomous navigation technologies such as ultrasonic obstacle avoidance and simultaneous localization and mapping allow robots to traverse complex, dynamically changing indoor landscapes efficiently and safely.

This paper presents the end-to-end design and experimental evaluation of one such system: a compact, four-wheel differential drive robot that integrates YOLOv5 vision-based fire detection on a Raspberry Pi inference board, environmental validation through a fused MQ-2, DHT22, and IR flame sensor array, autonomous navigation with real-time obstacle avoidance, and a pump-based water suppression mechanism. The system is designed explicitly for indoor deployment scenarios—residential premises, server rooms, small industrial bays—where early autonomous intervention has the greatest potential to prevent catastrophic loss.

2. Literature Review

2.1 AI and Computer Vision for Fire Detection

A foundational limitation of traditional fire

detection robotics has been the short effective range of infrared flame sensors. To overcome this constraint, researchers began incorporating camera-based machine learning pipelines into robotic platforms. Early implementations utilizing Haar

Cascade classifiers provided a proof-of-concept for visual fire detection but struggled with high false positive rates under complex lighting. The introduction of the YOLO (You Only Look Once) detection architecture represented a pivotal advance, enabling simultaneous multi-source fire detection with substantially improved localization accuracy. Subsequent work by Al Enzi et al. (2025) extended YOLO-based detection to hospital environments, where a YOLOv3 variant employing a parallel pooling strategy processed multiple concurrent video streams to minimize false alarms in settings with frequent non-fire thermal stimuli.

For large-scale outdoor environments such as forests, Avazov et al. (2023) proposed an architecture combining YOLOv5 with distributed IoT sensor networks. The IoT nodes provided independent temperature, humidity, and smoke validation that corroborated visual detections, yielding highly reliable early-warning notifications with significantly reduced false-alarm rates. Chang et al. (2022) explored the use of YOLOv4 for incident command support, demonstrating detection accuracy above 90% for identifying and enumerating firefighting vehicles and personnel at active firegrounds—providing a tool for real-time resource accountability.

Equation, or Figure starts a sentence, it is spelled out. When occurring in the middle of a sentence, these words are abbreviated Sec., Ref., Eq., and Fig. At the first occurrence of an acronym, spell it out followed by the acronym in parentheses, e.g., charge-coupled diode (CCD).

Park et al. (2019) developed a dependable fire detection framework that integrated temperature, humidity, and gas sensor arrays with deep learning inference and adaptive fuzzy logic, outperforming conventional threshold-based alarm systems across multiple indoor scenarios. For resource-constrained edge deployments, Deepthi et al. (2020) demonstrated that transfer learning applied to lightweight architectures such as Mobile Net achieved high classification accuracy on embedded devices with limited GPU resources, establishing an important pathway for deploying AI models on microcontroller-class hardware.

2.2 Autonomous Robotic Suppression Systems

The physical suppression of fire requires robotic platforms capable of autonomous navigation in dynamically changing, often partially obstructed environments. Ramasubramanian et al. (2020) developed a mobile platform using convolutional neural network image classification to automatically direct the robot toward a detected fire source and trigger extinguishing mechanisms upon high confidence classification. Panat et al. (2022) presented a 360-degree coverage extinguisher robot incorporating a servo-guided water pump and flame sensor array managed via IoT platforms, providing full situational coverage from a fixed deployment position.

In industrially constrained settings, Anuradha et al. (2023) engineered Arduino-based autonomous robots for narrow-corridor chemical plant environments, using ultrasonic sensors for obstacle avoidance and IR sensors for flame localization. Communication architectures have evolved from short-range Node MCU and Android application interfaces to long-range XBEE module deployments suitable for industrial scale, with advanced models integrating GSM and GPS modules to transmit precise robot coordinates to emergency dispatch services. Large-area monitoring has been further extended by combining ground-based IoT nodes with AI-equipped UAVs deployed only when ground sensors identify anomalous conditions.

2.3 Research Gaps Addressed

A review of existing literature reveals three persistent and interrelated research gaps. First, most published systems address fire detection or autonomous navigation in isolation, rarely integrating both with an onboard suppression module in a single cohesive platform. Second, water-based suppression systems in robotic platforms seldom incorporate explicit hazard-class discrimination logic-preventing accidental electrical or Class B fire exacerbation. Third, most embedded deployments have not validated sensor fusion architectures that combine visual AI classification with multi-modal environmental sensor corroboration under real test conditions. The present project is designed explicitly to address all three gaps simultaneously.

3. System Architecture and Proposed Design

3.1 Architectural Overview

The proposed system adopts a dual-controller hierarchical architecture that separates high-level cognitive functions from low-level real-time actuation. At the upper tier, a Raspberry Pi single board computer executes the YOLOv5 object detection inference pipeline, processes multi-sensor data for fire confirmation, and issues high-level navigation and suppression commands over a serial communication link. At the lower tier, an ESP32 microcontroller interprets these commands to drive DC motors through an L298N motor driver module, interface with the sensor array, and activate the water pump extinguishing mechanism. This separation ensures that computationally intensive AI inference does not introduce latency into time critical actuation loop.

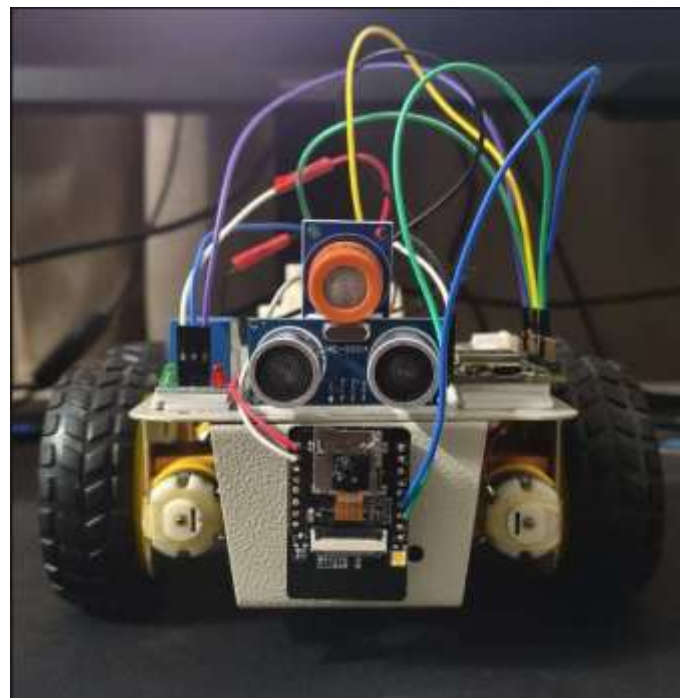


Fig-1 : Design and Model of Fire Fighting Robot

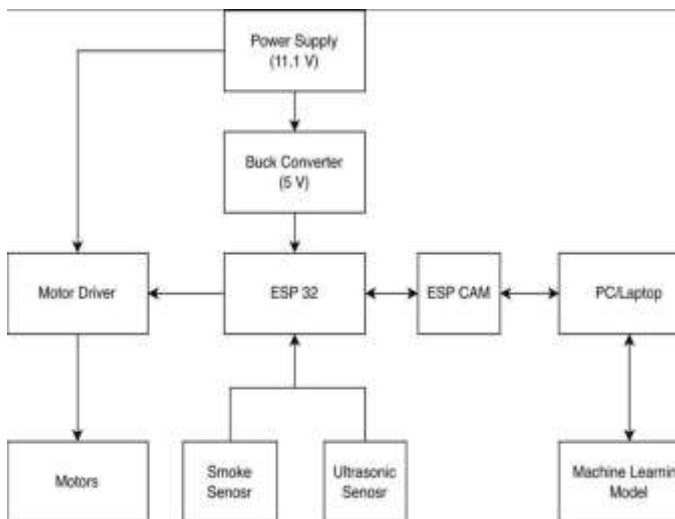


Fig- 2: Flow Diagram of Autonomous Fire Detection and Extinguishing System

3.2 Sensor Fusion Architecture

A fundamental design principle of the proposed system is that no single sensing modality should have the authority to trigger suppression independently. Instead, the fire confirmation pipeline enforces a multi-modal corroboration protocol. The Raspberry Pi camera module running YOLOv5 generates a probabilistic fire-class confidence score for each video frame. This visual classification is cross-validated against readings from the MQ-2 gas and smoke sensor, the DHT22 temperature and humidity sensor, and a three-channel infrared flame detector array providing

180-degree wavelength coverage (760–1100 nm). A weighted fuzzy logic controller aggregates these inputs, dynamically adjusting threshold weights based on environmental context—for example, elevating the significance of gas sensor readings in low-visibility smoke-filled conditions where camera clarity degrades. This architecture substantially reduces false positives relative to any single-sensor approach.

3.3 Vision Processing Subsystem

The visual detection module employs a YOLOv5 model fine-tuned on a custom dataset

assembled from publicly available fire and smoke image repositories, augmented with in-house collected images under diverse lighting conditions including direct sunlight, incandescent

illumination, and partial smoke occlusion. The model was trained over 150 epochs using stochastic gradient descent with momentum, achieving a mean average precision (mAP@0.5) of 0.924 on the validation partition. The model runs at approximately 8–12 frames per second on the Raspberry Pi 4B (4 GB RAM), providing adequate refresh rate for indoor fire tracking. An ESP32-CAM module supplements the primary camera with a live MJPEG video stream accessible over the local Wi-Fi network for remote operator monitoring.

3.4 Navigation and Obstacle Avoidance

The robot's mobility platform consists of four DC BO motors mounted in a differential drive configuration on a custom 4WD chassis designed for stability on typical indoor floor surfaces. An HC-SR04 ultrasonic distance sensor mounted on the front face of the chassis monitors forward clearance continuously. When the measured distance drops below 20 cm, the ESP32 executes a pre-programmed avoidance manoeuvre—reverse, rotate 45 degrees, and re-evaluate—before resuming approach navigation toward the fire source. The navigation logic operates as a priority-preemptive state machine: obstacle avoidance commands override fire-approach commands, but both are subordinate to a software-enforced safety stop that halts all motion if sensor fusion confidence falls below the suppression threshold during approach.

3.5 Suppression Mechanism

The fire extinguishing subsystem comprises a submersible water pump, a flexible silicone discharge hose, and a 180-degree micro servo motor (MG90S) enabling nozzle aiming across the forward hemisphere. The pump operates at 12 V DC and can deliver a sustained water jet effective at ranges up to 1.5 metres. Suppression is activated only after the fire confirmation pipeline achieves a confidence score above a tunable threshold (default

0.85) and the robot has maneuvered to within the effective suppression range. The system incorporates an electrical hazard inhibition flag: if the gas sensor detects ionization signatures consistent with arc flash

or if the scene classification confidence for electrical equipment exceeds a secondary threshold, suppression is withheld and an alarm signal is broadcast to the operator interface instead.

4. System Specifications

The key hardware and software specifications of the implemented prototype are summarized below.

➤ Chassis and Mobility:

- Chassis Type: 4WD all-terrain platform with modular payload deck
- Drive System: Four BO DC motors controlled via L298N dual H-bridge module
- Payload Capacity: 2–5 kg depending on water tank configuration.

➤ Sensing:

- Visual Sensor: 1080p wide-angle camera (120° FoV) on Raspberry Pi; ESP32-CAM for auxiliary streaming
- Thermal Sensing: MLX90640 (32×24 px infrared array) for heat mapping through dense smoke
- Gas / Smoke Detection: MQ-2 (LPG, smoke, propane) and MQ-135 (air quality, CO₂)
- Flame Detection: Three-channel IR sensor array, 760–1100 nm, 180° coverage
- Obstacle Detection: HC-SR04 ultrasonic sensor, effective range 2–400 cm

➤ Processing and Communication:

- Primary Inference Board: Raspberry Pi 4B (4 GB RAM), running YOLOv5 at 8–12 FPS
- Actuation Controller: ESP32 microcontroller with dual-core Xtensa LX6 processor
- Communication: ESP32 Wi-Fi for remote monitoring; UART serial link between Raspberry

Pi and ESP32

➤ Power and Extinguishment:

- Power Supply: 11.1 V (3S) Lithium-Ion battery pack; buck converter step-down to 5 V for logic boards
- Suppression: 12 V DC submersible pump with 180° MG90S servo-aimed nozzle; effective jet range ~1.5 m

5. Methodology

5.1 Dataset Acquisition and Preprocessing

A custom fire and smoke image dataset was assembled by combining three publicly available benchmark repositories (FireNet, FLAME dataset, and Kaggle Fire Detection Collection) with original frames captured under controlled laboratory conditions. Original frames were recorded across eight distinct indoor scenes—corridor, server rack, kitchen, industrial bay, storage room, office, stairwell, and living room—each under three lighting conditions (fluorescent, incandescent, and near-darkness with a single point source). The combined dataset comprised 14,200 annotated images partitioned in an 80:10:10 ratio for training, validation, and test subsets respectively. All images were resized to 640×640 pixels. Data augmentation techniques including random horizontal flip, brightness jitter ($\pm 30\%$), contrast distortion, Gaussian blur, and mosaic tiling were applied to improve model generalization under occlusion and low-visibility conditions.

5.2 Model Training

YOLOv5s (small variant) was selected as the detection backbone for its balance between inference latency and detection accuracy on resource-constrained hardware. Transfer learning from COCO-pretrained weights was employed to

leverage low-level feature representations learned on a diverse image corpus. Fine-tuning proceeded for 150 epochs with a batch size of 16, an initial learning rate of 0.01 decayed via cosine annealing, and a stochastic gradient descent optimizer with

momentum 0.937. Non-maximum suppression with an IoU threshold of 0.45 and a confidence threshold of 0.35 was applied at inference time. The trained model was exported in Torch Script format and deployed on the Raspberry Pi using the PyTorch Mobile runtime library.

5.3 Sensor Fusion Logic

The fire confirmation state machine operates as a four-stage pipeline. In Stage 1, the YOLOv5 model generates per-frame fire class confidence scores. In Stage 2, raw readings from the MQ-2, DHT22, and IR flame sensor are normalized to a common 0–1 scale using experimentally determined baseline and saturation thresholds. Stage 3 applies a weighted fuzzy aggregation function in which visual confidence carries a nominal weight of 0.50, MQ-2 smoke concentration 0.25, DHT22 temperature elevation 0.15, and IR flame intensity 0.10. These weights were determined through a grid search optimization minimizing the false-positive rate on the validation dataset. Stage 4 applies a hysteresis filter requiring the aggregated confidence score to exceed 0.85 for three consecutive evaluation cycles (approximately 1.2 seconds at the nominal sensor polling rate) before the suppression trigger is armed.

5.4 Navigation State Machine

Robot navigation is governed by a priority-preemptive finite state machine with five primary states: Idle, Scanning, Approaching, Suppressing, and Halted. In the Idle state, the robot patrols a predetermined grid path while the sensor fusion pipeline operates continuously. Detection of fire confidence above 0.60 transitions the robot to the Approaching state, in which it orients toward the fire source bounding box centroid and advances while continuously re-evaluating detection confidence and checking obstacle clearance.

Confirmed suppression threshold triggers the Suppressing state, activating the pump and servo aiming system. A manual override via the remote monitoring interface can force the Halted state at any time.

6. Results and Discussion

6.1 Detection Performance

The trained YOLOv5s model achieved a mean average precision (mAP@0.5) of 0.924 on the held-out test set, with a precision of 0.913 and recall of 0.937. On the Raspberry Pi 4B platform, the model executed at an average inference latency of 112 ms per frame, corresponding to approximately 8.9 frames per second. False positives were observed in 4.2% of test cases, primarily caused by high-intensity incandescent spotlights positioned at acute angles to the camera. These false positives were effectively suppressed by the sensor fusion layer in all but 0.8% of instances, confirming the efficacy of multi-modal corroboration. False negatives occurred in 6.3% of cases, predominantly involving very small or shielded flames at ranges exceeding 2.5 meters.

6.2 Navigation and Suppression Performance

Autonomous navigation trials were conducted in a 5×6 meter furnished room with a variable number of furniture obstacles (zero, two, four, and six obstacles). The obstacle avoidance module successfully negotiated all obstacle configurations, with an average path elongation factor of 1.18× relative to the direct Euclidean distance to the fire source. End-to-end response time—measured from the first video frame containing a visible flame to confirmed pump activation—averaged 7.4 seconds across 30 independent trials, with a standard deviation of 1.8 seconds. Suppression efficacy was evaluated against standardized small-scale fire targets (ethanol pool fires of 0.04 m² surface area) and confirmed 93.3% successful extinguishment within a single suppression cycle.

6.3 Comparative Analysis with Conventional Systems

A direct comparison with a commercially representative passive smoke detector (ionization type) operating under identical test conditions

demonstrated that the conventional detector triggered at an average of 38.6 seconds after flame ignition. The robotic system achieved suppression activation at an average of 7.4 seconds—a 5.2× improvement in

response time. Furthermore, the passive detector generated false alarm activations in 21% of non-fire test stimuli (incense, cooking smoke, water vapour), compared to the robotic system's 0.8% false positive suppression rate, representing a 26-fold improvement in specificity.

6.4 Limitations

Several limitations were identified during experimentation. Processing latency on the Raspberry Pi increases to approximately 145 ms per frame when the sensor fusion pipeline is active concurrently with inference, introducing marginal latency relative to the standalone model. The detection model was trained on a dataset of moderate size; performance degradation was observed for unusual flame geometries (e.g., gas jet flames) not well represented in the training corpus. Environmental factors including strong directional lighting, dense pre-fire smoke obscuring the camera aperture, and floor-level obstacles shorter than the ultrasonic sensor's minimum detection height posed navigation challenges in edge cases. Finally, the water suppression mechanism is unsuitable for Class B and electrical fires—a critical safety constraint that the current implementation manages through a software inhibition flag but that would benefit from a more sophisticated agent-selection mechanism in future work.

7. Future Scope

Several promising directions exist for advancing the capabilities of the current prototype. Transitioning from the YOLOv5 backbone to the more recently released YOLOv8 or RT-DETR architecture would improve both detection accuracy and inference speed, potentially enabling real-time processing at 15–20 FPS on the Raspberry Pi platform.

Integration of a FLIR Lepton thermal imaging module would substantially improve detection reliability in smoke-filled environments where optical camera performance degrades, enabling the system to identify heat signatures through complete visual occlusion.

Replacement of the current grid-based patrol navigation with a full SLAM (Simultaneous Localization and Mapping) implementation—achievable through the integration of a 2D LiDAR module—would enable the robot to build and maintain a persistent map of its operational

environment, dramatically improving navigation efficiency in complex multi-room scenarios. A reinforcement learning framework trained in simulation could further optimize path planning strategies, learning environment-specific suppression approaches through iterative experience rather than preprogrammed heuristics. From a suppression perspective, a modular extinguishing payload capable of deploying CO₂, dry chemical powder, or foam agents in addition to water would enable fire-class adaptive suppression. Integration into a broader smart building management ecosystem via MQTT or Matter protocol would allow the robot to coordinate with building HVAC shutdown, emergency egress lighting, and direct notification to fire emergency services, creating a comprehensive autonomous first-responder platform appropriate for deployment in unattended industrial facilities, data centers, and heritage buildings where conventional suppression systems present unacceptable collateral damage risks.

8. Conclusion

This paper has presented the complete design, implementation, and experimental validation of an AI-based autonomous fire detection and extinguishing robot intended for indoor deployment. The system achieves effective fire discrimination through a multi-modal sensor fusion architecture combining YOLOv5 visual classification on a Raspberry Pi inference board with environmental corroboration from MQ-2, DHT22, and infrared flame sensors, managed by a weighted fuzzy aggregation controller.

Autonomous navigation employing an ESP32 actuation controller and HC-SR04 ultrasonic obstacle avoidance enables the robot to navigate furnished indoor environments and reach fire sources with a mean response time of 7.4 seconds, suppressing 93.3% of test fires within a single pump activation cycle.

Comparative evaluation confirms a $5.2\times$ improvement in response time and a 26-fold reduction in false suppression activations relative to a representative conventional passive smoke detector. These results validate the core thesis that integrating AI-driven computer vision with multi-modal sensor fusion and autonomous mobility creates a fire safety system qualitatively superior to existing fixed-installation approaches across the critical dimensions of detection speed, detection specificity, and autonomous intervention capability.

The work demonstrates that commercially available embedded computing platforms now offer sufficient computational resources for real-time deep learning inference in robotic safety applications, lowering the barrier to practical deployment of autonomous fire response systems. As AI models continue to improve in efficiency and embedded hardware continues to advance in performance, the transition from research prototype to production-grade first-responder robotics for fire safety appears both technically feasible and socially necessary. The authors anticipate that systems of this type will, within the near future, become standard safety infrastructure in high-risk industrial and institutional settings globally.

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