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

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[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 YOLO11n 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

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[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.

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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.

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• 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 I²C 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.

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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.

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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.

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Training configuration was as follows:

• Input size: 640 × 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 layers448 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.

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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.

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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 CO₂ 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.

References

[1] Y. He, J. Hu, M. Zeng, Y. Qian, and R. Zhang, “DCGC-YOLO: The Efficient Dual-Channel

Bottleneck Structure YOLO Detection Algorithm for Fire Detection,” IEEE Access, vol. 12.

Institute of Electrical and Electronics Engineers (IEEE), pp. 65254–65265, 2024. doi:

10.1109/access.2024.3385856.

[2] T. Khan, “A Smart Fire Detector IoT System with Extinguisher Class Recommendation Using

Deep Learning,” IoT, vol. 4, no. 4. MDPI AG, pp. 558–581, Nov. 25, 2023. doi:

10.3390/iot4040024.

[3] H. Alqourabah, A. Muneer, and S. M. Fati, “A smart fire detection system using iot

technology with automatic water sprinkler,” International Journal of Electrical and Computer

Engineering (IJECE), vol. 11, no. 4, p. 2994, Aug. 2021, doi: 10.11591/ijece.v11i4.pp2994-3002.

[4] S. Saponara, A. Elhanashi, and A. Gagliardi, “Real-time video fire/smoke detection based on

CNN in antifire surveillance systems,” Journal of Real-Time Image Processing, vol. 18, no. 3, p.

889â€“900, Nov. 2020, doi: 10.1007/s11554-020-01044-0.

[5] et al. Mondal, “Automating Fire Detection and Suppression with Computer Vision: A Multi-

Layered Filtering Approach to Enhanced Fire Safety and Rapid Response,” Springer Link, vol.

XX, no. X, pp. 1–12, 2023, doi: 10.1007/sXXXXX-XXX-XXXX.

[6] et al. Sharma, “An Integrated Fire Detection System Using IoT and Image Processing

Technique for Smart Cities,” Sustainable Cities and Society, vol. 61, p. 102332, 2020, doi:

10.1016/j.scs.2020.102332.

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[7] et al. Dua, “An Improved Approach for Fire Detection using Deep Learning Models,” in 2020

International Conference on Industry 4.0 Technology (I4Tech), IEEE, 2020, pp. 1–5. doi:

10.1109/I4Tech48345.2020.9112379.

[8] et al. Saponara, “Real-Time Video Fire/Smoke Detection Based on CNN in Anti-Fire

Surveillance Systems,” Journal of Real-Time Image Processing, vol. 18, pp. 889–902, 2021, doi:

10.1007/s11554-021-01101-4.

[9] Chetoui and A. Akhloufi, “Fire and Smoke Detection Using Fine-Tuned YOLOv8 and

YOLOv7 Deep Models,” Fire, vol. 7, no. 5, p. 220, 2024, doi: 10.3390/fire7050220.

[10] et al. Srinivasan, “Early Detection of Fire using YOLOv8 and Computer Vision,” in

Proceedings of the 7th International Conference on Inventive Computation Technologies

(ICICT), IEEE, 2024, pp. 1–7.

[11] et al. Khan, “A Smart Fire Detector IoT System with Extinguisher Class Recommendation

Using Deep Learning,” IoT, vol. XX, no. X, pp. 1–10, 2023, doi: 10.3390/iotXXXXX.

[12] et al. Dhiman, “Firefighting Robot with Deep Learning and Machine Vision,” International

Journal of Intelligent Systems and Applications (IJISA), vol. 14, no. 1, pp. 40–47, 2022, doi:

10.5815/ijisa.2022.01.04.

[13] et al. Alqourabah, “A Smart Fire Detection System Using IoT Technology with Automatic

Water Sprinkler,” International Journal of Electrical and Computer Engineering (IJECE), vol.

11, no. 4, pp. 3429–3437, 2021, doi: 10.11591/ijece.v11i4.

[14] et al. Pincott, “Indoor Fire Detection Utilizing Computer Vision-Based Strategies,” Journal

of Building Engineering, vol. 57, p. 104892, 2022, doi: 10.1016/j.jobe.2022.104892.

[15] et al. Wang, “Automatic Real-Time Fire Distance, Size and Power Measurement Driven by

Stereo Camera and Deep Learning,” Fire Safety Journal, vol. 131, p. 103658, 2023, doi:

10.1016/j.firesaf.2023.103658.

[16] et al. Huang, “A Combined Real-Time Intelligent Fire Detection and Forecasting Approach

Through Cameras Based on Computer Vision Method,” Process Safety and Environmental

Protection, vol. 159, pp. 49–60, 2022, doi: 10.1016/j.psep.2021.12.041.

[17] et al. Fengju, “Intelligent and Vision-Based Fire Detection Systems: A Survey,” Image and

Vision Computing, vol. 91, p. 103803, 2019, doi: 10.1016/j.imavis.2019.103803.

[18] Md. A. R. Chowdhury, R. Khandoker, and Md. M. Rahman, “Deep Learning-Based Fire

Detection: A Review,” Sensors, vol. 21, no. 20, p. 7004, 2021, doi: 10.3390/s21207004.

[19] A. Sharma, D. Soni, and H. Patel, “Smoke and Fire Detection Using Deep Learning: A

Survey,” International Journal of Image and Graphics, vol. 22, no. 2, p. 2250012, 2022, doi:

10.1142/S0219467822500124.

[20] T.-Y. Lin et al., “Microsoft COCO: Common Objects in Context,” in European Conference

on Computer Vision (ECCV), 2014, pp. 740–755.

[21] P. Micikevicius et al., “Mixed Precision Training,” in International Conference on Learning

Representations (ICLR), 2018.

[22] G. Jocher, A. Chaurasia, J. Qiu, and A. Stoken, “Ultralytics YOLO: Real-Time Object

Detection.” GitHub repository, 2023.

[23] B. Zoph, E. D. Cubuk, G. Ghiasi, T.-Y. Lin, J. Shlens, and Q. V. Le, “Learning Data

Augmentation Strategies for Object Detection,” in European Conference on Computer Vision

(ECCV), 2020, pp. 566–583.

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[24] S. Yun, D. Han, S. J. Oh, S. Chun, J. Choe, and Y. Yoo, “CutMix: Regularization Strategy to

Train Strong Classifiers With Localizable Features,” in IEEE International Conference on

Computer Vision (ICCV), 2019, pp. 6023–6032.

[25] S. J. Pan and Q. Yang, “A Survey on Transfer Learning,” IEEE Transactions on Knowledge

and Data Engineering, vol. 22, no. 10, pp. 1345–1359, 2010, doi: 10.1109/TKDE.2009.191.

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