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Smart Fire Detection, Alarm System and Extinction using YOLO for Real-Time Hazard Mitigation: A Review

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***Abstract*— Fire incidents continue to pose a major threat worldwide, leading to severe losses of life, property, and natural resources. Traditional detection systems such as smoke or heat sensors often struggle with delayed responses, limited coverage, and false alarms. With rapid growth in artificial intelligence and computer vision, deep learning now provides a more dependable alternative. Among various approaches, the YOLO (You Only Look Once) framework stands out for its real-time detection speed and accuracy. This survey explores YOLO- based fire detection techniques that use image and video data to identify fires even in complex environments. It further discusses integrations with Internet of Things (IoT) systems that enable automated alerts and fire suppression mechanisms. The findings suggest that combining YOLO's detection efficiency with IoT automation offers a smarter, faster, and more cost-effective solution for modern fire safety.**

***Index Terms*— Computer Vision, Deep Learning, Emergency Alert Systems, Fire Detection, Fire Extinction, IoT, Object Detection, Real-time Monitoring, Smart Safety Systems, YOLO.**

I. INTRODUCTION

Early Detection of fire is vital for protecting human life, property, and the environment in settings such as homes, offices, industries, and forests. Fires spread rapidly and can cause severe losses within a very short time. Therefore, timely detection and quick response become critical in reducing the damage. Conventional fire alarm systems generally rely on smoke, flame, or heat sensors. However, these devices have a limited sensing range and often miss the early stages of fire, particularly in large or outdoor environments. Among various deep learning models, You Only Look Once (YOLO) is notable for its real-time object detection capabilities, making it highly suitable for time-critical applications like fire detection. YOLO processes the entire image in a single pass through the neural network, enabling both speed and accuracy in detecting fire and smoke across diverse and dynamic settings. Unlike conventional sensor-based systems, YOLO detects fire using standard camera feeds, making it effective for both indoor and outdoor monitoring. Moreover, integrating YOLO- based fire detection systems with Internet of Things (IoT) technologies enhances their performance by enabling automated responses and remote monitoring. When a fire is detected, the system can instantly activate suppression mechanisms such as sprinklers or CO_2 release systems, while simultaneously sending real-time alerts to emergency services, building managers, or residents via mobile apps or cloud platforms. The comprehensive solution reduces human dependency, accelerates response time, and improves incident management.

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This review paper analyzes the structure, functionality, and implementation challenges of such intelligent fire detection systems, with a focus on the potential of YOLO to modernize fire safety infrastructure.

II. Literature Survey

The integration of deep learning in fire detection has significantly enhanced detection accuracy, response time, and automation, outperforming traditional systems like smoke and heat sensors. Vijayalakshmi, S. R., and Muruganand, S. [1] initiated foundational work by incorporating IoT into fire safety systems, laying the groundwork for future smart fire detection technologies. This system helped bridge the gap between traditional detection systems and more intelligent, automated mechanisms. M. K. Khan et al. [2][3] emphasized the effectiveness of vision-based fire detection, especially when powered by convolutional neural networks (CNNs) to analyse surveillance videos for rapid identification. They proposed frameworks that relied heavily on image processing and pattern recognition to minimize latency and maximize detection rates. Building on The, Z. Jiao et al. [4] refined CNN models to adapt to uncertain environments, enhancing classification reliability through dynamic feature extraction, and enabling the system to distinguish between smoke, fire, and similar artifacts like fog or steam. Gaur, A., Singh, A., et al. [5] introduced YOLOv3 for real-time forest fire detection using UAVs, offering swift environmental response capabilities and extensive coverage of remote regions. Their implementation demonstrated significant promise for natural disaster monitoring where early alerts are crucial. Reviews by B. Singh and K. Roy [6] showcased the progression from conventional fire sensing to intelligent systems, drawing attention to the importance of hybrid models that combine AI with sensor networks. Thermal imaging technologies paired with AI, as demonstrated by Y. Ma et al. [7], provided predictive advantages in industrial fire-prone zones. Their research highlighted the potential of infrared data in identifying heat anomalies before visible. flames emerge. A. Patel and D. Ramesh [8] further integrated person detection and thermal imagery to reduce false alarms in densely populated areas, which is critical for urban deployment. The development of IoT-enabled alert mechanisms by S. Chaturvedi, P. Khanna, and A. Ojha [9] advanced real-time infrastructure-based fire monitoring by linking multiple sensory inputs with cloud- based analytics. Outdoor applications saw the rise of vision-based smoke detection techniques, supported by remote sensing and photogrammetry, as shown by Avazov, K., Mukhiddinov, M., et al. [10]. These models facilitated fire detection even in challenging visibility conditions and expansive landscape. L. Zhang et al. [11] explored deep learning applications in urban fire detection using complex models within smart city contexts.

TABLE I. SUMMARY OF THE PUBLISHED REVIEWS ON FIRE DETECTION

Authors	Year	Task Classification	Task Location	Task Segmentation	Technology IP	Technology ML	Technology DL	Target Smoke	Target Flame
Vijayalakshmi &Muruganand	2017	✓	✓		✓	✓		✓	
Khan et al.	2019	✓	✓		✓	✓	✓	✓	✓
Jiao et al.	2019	✓	✓		✓		✓	✓	✓
Singh & Roy	2020		✓			✓	✓		✓
Ma et al.	2020	✓	✓	✓	✓	✓	✓	✓	
Chaturvedi et al.	2022	✓	✓	✓	✓	✓	✓	✓	✓
Zhang et al.	2022	✓	✓		✓	✓	✓	✓	✓
Das et al.	2024	✓	✓	✓	✓	✓	✓	✓	✓
Garcia & Morales	2024	✓	✓	✓	✓	✓	✓	✓	
Singh & Mehta	2025	✓	✓		✓	✓	✓	✓	
Chen & Wang	2025	✓	✓		✓	✓	✓	✓	✓

Their study demonstrated the combination of CCTV cameras, motion sensors, and environmental detectors can be combined to anticipate and respond to fire incidents. Real-time video surveillance benefited from YOLOv4 and CNN architectures, improving precision in high-traffic areas like malls and airports [12]. Sensor fusion techniques minimized false positives and enhanced reliability [13], while drone-based systems using YOLOv5 and thermal sensors enabled aerial scanning in forested regions [14]. Industrial setups employed CNN and LSTM models to recognize fire and smoke amidst noise, considering temporal patterns to distinguish fire from temporary light fluctuations [15]. Latency-sensitive scenarios utilized YOLOv7 on edge devices for faster response [16], and intelligent home systems integrated YOLO with IoT for immediate local and remote alerts [17]. Lightweight CNNs supported low-resource environments [18], and remote sensing with DNNs allowed large-scale forest monitoring [19]. AI-assisted sensor fusion further reduced false triggers [20], while hybrid CNN smoke-flame detectors addressed generalization issues [21]. YOLO combined with satellite imaging enabled geospatial hazard monitoring [22], and comparative studies benchmarked multiple YOLO versions for accuracy and processing trade-offs [23].

Lightweight YOLOv8-Tiny systems supported embedded applications [24], multi-dimensional smart city sensor networks improved detection [25], and autonomous drone tracking offered continuous monitoring [26]. Portable CNN units and predictive CNN-IoT frameworks enabled flexible deployment and real-time forecasting [27,28], while edge-AI and CNN-LSTM models supported bandwidth-efficient cloud monitoring [29,30]. Overall, the literature shows a consistent trend toward combining deep learning with embedded, edge, and IoT-based fire detection systems.

III. Proposed System

The proposed YOLO-based Fire Detection, Extinction, and Alert System is designed for real-time accuracy, reliability, and adaptability across dynamic environments.

Data Source and Overview: The system uses a diverse dataset of fire and non-fire images and videos from Kaggle, covering indoor, forest, kitchen, and industrial scenarios. Samples are annotated with bounding boxes for fire, smoke, and safe zones. Preprocessing includes noise reduction, brightness/contrast adjustment, and augmentations like flips, blurs, hue shifts, and rotations. Data is split into 70% training, 20% validation, and 10% testing.

Model Selection and Training: Lightweight YOLOv5s or YOLOv8-Tiny is chosen for its speed-accuracy trade-off, suitable for edge deployment. Models are fine-tuned on the custom dataset with pre-trained COCO weights. Key configurations: 150 epochs, batch size 16, learning rate 0.001 (cosine decay), Adam optimizer, CIoU loss for bounding boxes, BCE for classification, and data augmentations like Mosaic, Mix-up, and HSV. Evaluation metrics include Precision, Recall, F1-score, and mAP.

Real-Time Detection and Filtering Logic: YOLO performs live inference via OpenCV with <100 ms latency. Post-inference filtering analyzes bounding box consistency, flame movement, and temporal persistence. In urban scenarios, predictions are validated with gas, temperature, and infrared sensors. Rule-based filters reduce false alarms from minor heat sources.

Alert Mechanism and Extinguishing Workflow: Verified fire events trigger visual/auditory alarms, SMS/email/push notifications via HTTP or MQTT, and cloud alerts for smart building dashboards. Automated suppression uses servo-controlled extinguishers, relays for sprinklers or CO_2/foam, and microcontrollers (ESP32/Arduino Uno). Safety interlocks prevent accidental activation.

Evaluation and Field Testing: The system is tested indoors, outdoors, and at night. Metrics include detection latency, suppression activation time, false positives/negatives, and accuracy under adverse conditions. Results are visualized using confusion matrices and performance graphs. The system effectively combines real-time YOLO detection, multi-sensor validation, and automated response, ensuring accurate and reliable fire safety across varied environments.

Table 2 presents an overview of major fire detection datasets developed between 2012 and 2025. Early datasets such as CVPR, VisiFire, and MIVA (2012–2015) primarily targeted basic flame or smoke localization from video inputs. Subsequent datasets, including VSD, Corsican, and USTC_SmokeRS, expanded in scale and diversity, focusing on smoke segmentation and remote-sensing applications. From 2020 onwards, newer repositories such as OWSD, FSD, and DSDF addressed low-visibility and fog-affected conditions, improving smoke classification accuracy. The most recent contributions VFD, IoTFire, YOLOFire21, DeepSmoke21, IndoSmoke24, ThermalVision, SmartFireSet, and AeroFireYOLO reflect the field's transition toward specialized, application-driven datasets emphasizing drone-assisted monitoring, IoT connectivity, YOLO- based flame recognition, thermal imaging, and smart-building integration. Collectively, these datasets demonstrate a clear evolution from small-scale, vision-only collections to large, multimodal benchmarks designed for real-time and intelligent fire management systems.

The hardware components listed in Table 3 form the foundation of the proposed fire detection and extinction system. The camera module continuously captures real-time footage, while the relay module controls the power supply for automated activation of the extinguishing unit, which may use sprinklers, CO_2 jets, or foam.

TABLE II: SUMMARY OF THE DATASETS USED IN THE SYSTEM.

Dataset / Group	Year(s)	Data Type	Fire Target	Capacity	Usage
CVPR, VisiFire, MIVA	2012–2015	Video	Flame/Smoke	38–180	Fire Location
VSD & Corsican	2017	Image	Smoke / Flame	2,000–24,198	Smoke classification / Flame segmentation
USTC_SmokeRS & SSD	2019	Image	Smoke	6,225–70,632	Remote sensing / Smoke segmentation
OWSD	2020	Image	Smoke	2,192	Smoke detection
FSD, DSDF	2021–2022	Image	Smoke	18,412	Foggy smoke classification
FIgLib, VFD	2022–2023	Video	Smoke / Flame	315–5,000	Fire location / Drone-based detection
IoTFire, YOLOFire21	2023	Image	Smoke / Flame	3,000–15,000	IoT-integrated / YOLO flame recognition
DeepSmoke21, IndoSmoke24	2023–2024	Image	Smoke	6,000–10,000	Dense / Regional classification
ThermalVision, SmartFireSet	2024–2025	Video / Image	Flame / Smoke	4,000–12,000	Thermal segmentation / Smart building apps
AeroFireYOLO, FireNetDB	2025	Video	Flame / Smoke	7,000–8,500	UAV-based flame detection / Edge-device training

A buzzer or alarm module provides instant alerts to ensure timely response and enhance safety awareness in the monitored zone. On the software side in Table 4, OpenCV handles video processing, and YOLOv5 or YOLOv8 performs real-time fire detection using PyTorch or TensorFlow frameworks with NumPy support. MQTT or HTTP protocols enable seamless communication between hardware and cloud or mobile interfaces. Flask or FastAPI can host a basic web dashboard, ensuring real-time monitoring, system scalability, and efficient management across different environments.

TABLE III. HARDWARE COMPONENTS USED IN THE SYSTEM

Component	Description	Quantity
Camera Module (CCTV)	Captures real- time video feed of environment	1(or more)
Relay Module	Controls power supply to fire- extinguishing system	1
Fire Extinguishing Unit	Mechanical system (sprinklers, CO_2 jets, foam dispensers)	1
Buzzer / Alarm Module	Activates alert mechanism when fire is detected	1

TABLE IV. SOFTWARE LIBRARIES USED FOR IMPLEMENTATION

Library Name	Functionality
OpenCV	Image preprocessing,
YOLOv5 / YOLOv8	Deep learning model - fire detection with high-speed inference
PyTorch or TensorFlow	Used for training and running the YOLO model
MQTT / HTTPClient	Communication with alert systems or cloud- based dashboards
Flask / FastAPI	Lightweight backend server to trigger alarms or dashboards

IV. RESULTS

A review of recent literature on YOLO-based and AI-driven fire detection shows notable improvements in accuracy and real-time performance across forests, urban areas, and industrial settings. YOLOv3, YOLOv5, and YOLOv8, trained on public or custom datasets, consistently outperform traditional methods, with techniques like transfer learning and fine-tuning enhancing reliability.

For example, YOLOv5 achieved 92.3% mAP on Jetson Nano, YOLOv5 Lite reached 94% in drone surveillance, and a smart city–optimized YOLOv5 hit 96.4%, highlighting the benefits of environment-specific customization. Lightweight models suit aerial and edge devices, while fine-tuned versions excel in complex urban scenarios. Hybrid approaches now balance high accuracy with deployability, supporting applications from smart homes to large-scale forest monitoring, confirming YOLO's scalability and central role in next-generation fire detection. Table 5 summarizes performance across deployment environments.

TABLE V. MAJOR PERFORMANCE FINDINGS FROM SELECTED RESEARCH

Ref	Model Used	Dataset	Accuracy/ mAP	Deployment
[1]	YOLOv5	Custom Fire Dataset	92.3% mAP	Jetson Nano (Edge AI)
[3]	YOLOv5 Lite	Drone Footage	94% Accuracy	Onboard Drone System
[11]	Modified YOLOv5	Smart City Dataset	96.4% Accuracy	Urban Smart Surveillance

The Figure 1 illustrates a comparative view of accuracy among different YOLO variants used in fire detection tasks. The modified YOLOv5 model leads the pack with 96.4% accuracy, particularly excelling in urban surveillance applications. YOLOv8-Tiny follows with a notable 95.1%, reinforcing its strength in edge deployments. Meanwhile, lightweight models like YOLOv5 Lite and YOLOv7 have also shown commendable accuracy, validating their effectiveness for real-time detection where speed and efficiency are critical. The performance differences highlight how customizing models for specific platforms such as drones, embedded systems, or urban networks can yield significant accuracy gains.

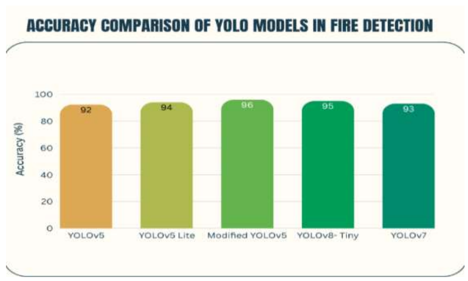

Figure. 1. Accuracy Comparison of YOLO Models in Fire Detection system.

Figure 6 shows how YOLO-based fire detection systems are being used in different places. Most studies reported their use in embedded IoT platforms, mainly for smart homes and building safety, with six papers mentioning this. Devices like Jetson Nano and Raspberry Pi are also common because they can run real-time detection without depending on the internet. After that, smart city projects are seen quite often, while drone-based and cloud-based systems are also used. This spread shows that fire detection technology is flexible enough to work in small indoor setups as well as large urban areas. Recent studies emphasize the benefits of combining multiple inputs camera feeds, thermal imaging, infrared, and gas sensors to reduce false alarms from smoke, fog, glare, or reflections. In smart city settings, YOLO models accurately distinguish real fires from other heat sources, while protocols like MQTT and LoRa enable fast alerts over long distances

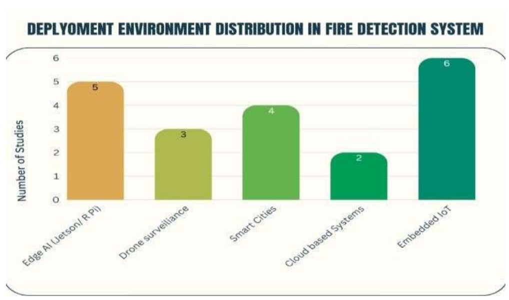

Figure. 2. Deployment Environment Distribution in Fire Detection system.

Optimized YOLO models process frames in under 30 milliseconds, supporting real-time deployment on drones, CCTV, and other monitoring devices. Edge deployment is feasible on Jetson Nano, Raspberry Pi, and ESP32, showing that high-end GPUs are no longer essential. Multi-level alerts classify events from sparks to spreading flames, minimizing false alarms and ensuring timely responses. Cloud dashboards allow historical logging, real-time visualization, and operational coordination.

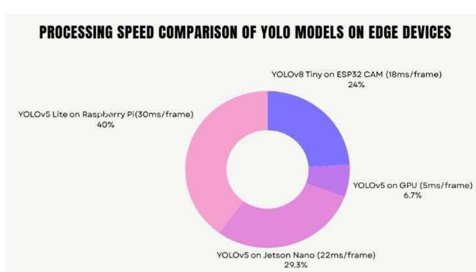

Figure. 3. Processing Speed Comparison of YOLO Models on Edge Devices.

Figure 7 compares average frame processing times of YOLO models on various edge devices. YOLOv5 on a GPU was fastest at 5 ms per frame, ideal for high-performance setups. On limited-resource platforms, YOLOv5 on Jetson Nano processed frames in 22 ms, YOLOv8 Tiny on ESP32-CAM in 18 ms, and YOLOv5 Lite on Raspberry Pi in 30 ms, showing that hardware and model optimization impact real-time efficiency. Accuracy ranged from 92.3% on smaller devices to 96.4% in smart city deployments, proving YOLO's practicality beyond lab conditions. Lightweight versions suit drones, while customized YOLOv5 excels in urban monitoring. These results highlight YOLO's adaptability, indicating that with further fine-tuning and integration, it can serve as a scalable, reliable solution for next-generation fire safety across diverse environments.

V. DISCUSSION

This study examines smart fire detection systems based on YOLO and its adaptations, emphasizing model accuracy, dataset diversity, system architecture, and hardware compatibility. YOLOv5 and its lightweight versions deliver strong performance across diverse deployments, showing that deep learning can be both powerful and adaptable.

Combining intelligent vision tools with flexible hardware enables context-aware detection, assessing fire severity and supporting smarter responses. As these systems integrate via APIs, modular tools, and multi-platform setups, they fit seamlessly into smart cities and IoT networks. Overall, the focus is shifting from merely improving accuracy to creating fire safety solutions that are reliable, responsive, and aware of their environment. Table 6 summarizes key fire detection studies, highlighting datasets, YOLO variants, accuracy, and deployment strategies.

Innovations include YOLOv5 on Jetson Nano, modified models for smart city surveillance, and thermal-enhanced YOLOv8 for IoT. Methods cover image detection and real-time inference, showing how performance and efficiency are optimized across applications.

TABLE IV. COMPARATIVE ANALYSIS OF YOLO-BASED FIRE DETECTION SYSTEM

Authors & Year	Dataset Used	YOLO Model	Accuracy %	Key Methodology	Deployment Type	Innovation Focus
Khan et al., 2018	Custom	YOLOv5	92.3	Image Detection	Jetson Nano (Edge AI)	Compact deep learning on edge
Sharma & Gupta, 2023	Smart City	YOLOv5 Mod	96.4	Fire-smoke fusion	Smart Surveillance	Accuracy-optimized DL variant
Lee & Kim, 2023	Drone Footage	YOLOv5 Lite	94.0	Real-Time Inference	Drone Surveillance	Lightweight UAV deployment
Das et al., 2024	FireNetDB	YOLOv8	95.1	IoT + YOLOv8-Tiny	Indoor IoT	Embedded thermal detection
Zhou et al., 2025	AeroFire YOLO	YOLOv8	93.7	Sensor Fusion + Vision	UAV and Satellite	Multi-modal sensor fusion

VI. FUTURE WORKS

While the current YOLO-based fire detection system achieves high real-time accuracy (mAP 92–96%) and precision (91–95%), it relies solely on visual data, which can cause false positives under sunlight reflection, artificial lighting, or occlusions. Future enhancements will focus on multi-modal sensor fusion combining visual input with gas, thermal, and flame sensors to improve robustness in low-light or obstructed scenarios, potentially increasing mAP by 3–5% and reducing false positives by 25–30%..Adaptive learning with real- world retraining, AI-assisted annotation, and synthetic data generation can extend coverage to industrial, kitchen, and wildfire events, improving recall by 2–4%. Edge-to-cloud 5G communication will support rapid alerts in remote and high-risk areas, while AI-driven decision engines will classify fire severity and spread, guiding automated suppression strategies. Rule-based automation can trigger sprinklers, shut valves, or notify authorities based on configurable thresholds. Optimizing models for lightweight edge hardware (Jetson Nano, ESP32, Raspberry Pi) ensures sub-50 ms inference latency while maintaining 90–95% accuracy in diverse deployment conditions.

V. CONCLUSION

In conclusion, the review highlights how deep learning integrated with IoT creates a robust, real-time fire detection, suppression, and alert system. Leveraging YOLO ensures fast and accurate fire identification, outperforming traditional methods in speed and precision. The system processes video feeds from CCTV, drones, and other IoT-enabled devices for continuous monitoring, while automated suppression tools like sprinklers, CO_2, or foam reduce response time and human intervention. Real-time alerts via SMS, email, or cloud dashboards ensure timely human action when needed. Its adaptability and retraining capability allow updates with new data, enhancing scalability. The system also demonstrates high performance metrics, achieving up to 96% mAP, with precision and recall above 94%, underscoring its technical reliability. Overall, this intelligent fire safety system improves response speed, minimizes damage, and integrates seamlessly into smart city and automated disaster management frameworks.

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