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Full Length Article

Enhancing Fire Detection With Yolov10: Advanced Techniques For Flame And Smoke Recognition

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ABSTRACT

Fire detection has become a critical research area due to its importance in protecting human life, infrastructure, and environmental resources. Traditional fire detection systems such as smoke sensors and heat alarms are often limited by delayed response, false alarms, and poor performance in large or complex environments. With the increasing use of surveillance cameras in industries, public spaces, forests, and residential areas, vision-based fire detection has emerged as an effective solution for early fire identification.

This research presents a deep learning-based approach for real-time flame and smoke detection using the YOLOv10 (You Only Look Once) object detection model. The proposed system improves detection accuracy by addressing challenges such as cluttered backgrounds, low visibility, varying fire intensities, overlapping objects, and smoke diffusion patterns. The system processes image and video streams, detects flames and smoke, tracks fire-related regions, and provides accurate localization through improved bounding box regression.

An enhanced feature extraction mechanism and attention-based learning strategy are incorporated to improve the model's focus on critical fire regions while reducing background interference. Experimental results show that the proposed YOLOv10-based system outperforms existing models such as YOLOv5s and YOLOv8 in terms of accuracy, precision, recall, and F1-score while maintaining real-time performance. The system offers a practical and scalable solution for industrial safety, smart surveillance, forest fire monitoring, and public safety applications.

Keywords: *Fire Detection, Flame Detection, Smoke Recognition, Deep Learning, Computer Vision, YOLOv10, Object Detection, Real-Time Monitoring, Smart Surveillance, Safety Systems.*

Introduction

Fire accidents remain one of the major causes of human loss, property damage, and environmental destruction across the world. Early fire detection is essential to reduce casualties and prevent large-scale disasters. Conventional fire detection systems mainly rely on smoke detectors, heat sensors, and manual monitoring. Although these systems are useful in indoor environments, they often fail in open areas, industrial zones, forests, and large public spaces where rapid and accurate detection is necessary.

Recent developments in artificial intelligence and computer vision have enabled automatic fire detection using surveillance cameras. Deep learning models, especially object detection algorithms, have shown strong capability in identifying flames and smoke from images and videos in real time. Among these models, YOLO-based architectures are widely used because of their high speed and strong detection performance.

However, fire detection remains challenging due to dynamic flame shapes, smoke diffusion, varying lighting conditions, occlusions, and cluttered backgrounds.

Therefore, there is a need for a more reliable and efficient system that can detect flames and smoke accurately under complex real-world conditions.

Problem Statement

Existing fire detection systems often struggle to detect flames and smoke accurately in challenging environments. Traditional sensor-based systems may produce delayed responses or false alarms, while many computer vision models focus mainly on object detection without handling difficult conditions such as low visibility, dense smoke, background confusion, and overlapping objects.

Many existing YOLO-based systems such as YOLOv5 and YOLOv8 provide good detection speed, but their accuracy decreases in complex fire scenarios. They may fail to distinguish smoke from clouds, fog, or dust, and often struggle with small flames or partially visible fire regions. This creates

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a major gap between detection performance and practical deployment.

Therefore, the central problem addressed in this work is the need for an accurate, real-time, and robust fire detection system capable of identifying both flames and smoke effectively in complex environments.

Significance of the Study

Early detection of fire hazards can significantly reduce damage, save human lives, and improve emergency response efficiency. Accurate flame and smoke detection helps industries prevent equipment damage, supports wildfire monitoring in forests, improves safety in residential buildings, and strengthens surveillance in public spaces.

By integrating deep learning-based detection with real-time monitoring systems, the proposed approach contributes to smarter and safer environments. It reduces dependency on manual observation and improves reliability compared to traditional detection systems.

Research Gap

A review of recent studies shows that many researchers have focused on improving fire detection using CNNs and YOLO-based models. However, most studies primarily focus on detection accuracy without addressing localization precision, robustness under adverse conditions, and real-time deployment.

Some systems improve flame detection but do not perform well in smoke recognition. Others handle smoke detection but fail under cluttered backgrounds or changing lighting conditions. Many approaches also lack advanced attention mechanisms that help the model focus on important fire-related regions.

These limitations highlight the need for a unified system that improves feature extraction, attention learning, and precise localization while maintaining real-time performance.Proposed Approach and Contributions

This study presents an enhanced fire detection system based on YOLOv10 for accurate flame and smoke recognition. The system processes image and video streams, detects fire-related objects, and provides precise localization in real time.

The main contributions of this work include the use of improved feature extraction for better fire pattern recognition, an attention-based mechanism for focusing on critical flame and smoke regions, and improved bounding box regression for accurate localization. The proposed system is designed to balance high accuracy with fast processing speed, making it suitable for real-world deployment.

Novelty of the Proposed Work

Recent advancements in fire detection systems have significantly improved flame and smoke recognition using deep learning and computer vision techniques. Several studies have focused on enhancing object detection accuracy using advanced YOLO architectures such as YOLOv5, YOLOv8, and lightweight CNN-based fire detection models. These approaches demonstrate strong performance in detecting visible flames under normal conditions. However, most of these works concentrate mainly on object detection tasks and do not fully address difficult challenges such as smoke diffusion, small flame regions, overlapping objects, and complex background interference.

Similarly, sensor-based fire monitoring systems have been widely used in industries and residential areas. While these systems improve early warning capability, they often depend only on smoke sensors or heat detectors and may produce delayed responses or false alarms. In many cases, these systems cannot provide visual confirmation or precise localization of fire regions. This creates a gap between detection and practical emergency response.

Research on smoke recognition has attempted to solve early-stage fire detection problems. Approaches based on CNN models and video analysis have shown promising results, but many of these methods are computationally expensive or designed for offline analysis, making them less suitable for real-time deployment in dynamic environments.

In addition, recent studies have explored lightweight and edge-based detection models to improve processing efficiency. While these models reduce latency and support deployment on resource-constrained devices, they primarily focus on speed optimization rather than complete system reliability and localization precision.

The novelty of this work lies in shifting the focus from simple flame detection to a complete intelligent fire detection framework. Unlike existing approaches, the proposed system introduces a dual flame-and-smoke recognition mechanism, where both visible flames and early smoke patterns are detected together. This improves early warning capability and reduces missed detections.

Another key novelty is the integration of an attention-based learning mechanism directly into the YOLOv10 detection pipeline. Instead of treating all image regions equally, the proposed system allows the model to focus on critical fire-related areas while suppressing irrelevant background noise. This improves detection performance in cluttered scenes and low-visibility conditions.

Furthermore, the system improves bounding box regression for more precise localization of flames and smoke, especially in dense environments where fire regions overlap with other objects. This increases reliability in industrial plants, forests, and public surveillance systems.

The proposed work also emphasizes real-time performance as a core design objective rather than a secondary outcome. While many existing studies report high detection accuracy, they do not address the practical constraints of live deployment. The proposed approach maintains a balance between speed and accuracy, making it suitable for continuous fire monitoring.

Table 1: Comparison of Existing Approaches with Proposed System

Aspect	Existing Works	ons in Existing Works	Proposed System
Primary Focus	Flame detection using YOLOv5, YOLOv8, CNN models	Focus mainly on visible flame detection only	Combined flame and smoke detection
Detection Capability	High accuracy for basic fire object detection	Difficulty in detecting smoke and small flames	Detects flames, smoke, and early fire patterns
Smoke Recognition	Some CNN-based smoke detection models	Weak performance in outdoor and cluttered scenes	Strong smoke recognition with attention mechanism
Attention Mechanism	Limited use of feature attention	Cannot prioritize critical fire regions	Integrated attention-based learning
Bounding Box Localization	Standard object localization methods	Poor precision in overlapping fire regions	Improved bounding box regression
Real-Time Performance	Fast detection in YOLO models	Accuracy drops in complex environments	High accuracy with real-time deployment
Environmental Robustness	Works well in normal conditions	Performance drops in smoke-heavy or low-light areas	Stable performance in difficult conditions
System Integration	Detection-focused systems only	Lack of complete monitoring framework	End-to-end fire detection framework
IoT Integration	Basic alert support in some systems	Delayed response and poor localization	Fast monitoring with practical deployment
Research Contribution Type	Mostly model-level improvements	Lack of complete system innovation	System-level innovation with full detection pipeline

Literature Review

Li et al. proposed an improved YOLO-based fire detection framework for real-time flame recognition in industrial environments. Their work focused on enhancing detection accuracy under normal lighting conditions and demonstrated that optimized YOLO architectures can improve fire monitoring performance.

Zhang et al. introduced a smoke detection model using deep convolutional neural networks for early-stage fire identification. Their approach improved smoke recognition accuracy, especially in indoor surveillance systems, but faced limitations in outdoor environments with complex backgrounds.

Wang et al. developed a YOLOv8-based flame detection system for smart surveillance applications. Their model improved feature extraction and reduced false positives caused by light reflections and background noise.

Ahmed et al. proposed a real-time fire detection system using IoT-enabled cameras and deep learning techniques. Their work highlighted the importance of combining surveillance cameras with intelligent detection models for faster emergency response.

Hassan et al. presented an attention-based YOLO model for fire and smoke recognition in industrial plants. Their system improved localization precision by focusing on critical fire regions and reducing unnecessary background interference.

Flores-Calero et al. conducted a systematic review of YOLO-based fire detection systems and identified major challenges such as low visibility, smoke diffusion, overlapping objects, and dataset limitations.

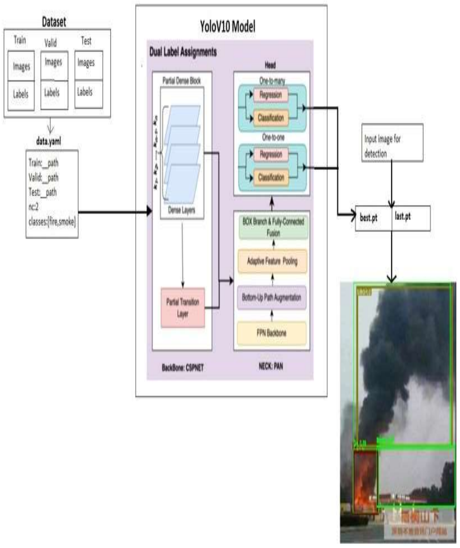
Kalva et al. proposed a smart surveillance fire monitoring system using YOLO and computer vision techniques.

Their work demonstrated practical implementation of deep learning models for real-time flame detection.

Khan et al. developed an intelligent fire surveillance system using deep learning-based anomaly detection. Their system improved fire detection accuracy and supported continuous monitoring in public spaces.

Ge et al. presented a survey on deep learning approaches for intelligent safety monitoring systems. Their work highlighted the importance of scalability, detection speed, and real-time deployment in modern fire detection applications.

Doshi and Yilmaz proposed motion and pattern-based anomaly detection for fire recognition in surveillance videos. Their study emphasized the importance of temporal information in identifying smoke spread and flame movement.



Sultani et al. introduced a framework for real-world anomaly detection in surveillance videos. Their approach has been widely adopted for abnormal event detection and inspired later fire detection research.

Alafif et al. proposed an AI-enabled IoT framework for smart safety monitoring systems. Their work showed how IoT integration improves real-time communication and emergency response efficiency.

Lv et al. developed a deep learning-based approach for hazard prediction using large-scale surveillance data. Their model supports better fire risk assessment and preventive monitoring.

Wang et al. presented a comprehensive survey on deep learning applications in intelligent safety systems. Their study discussed various models and highlighted challenges such as computational requirements and environmental complexity.

Dany Alfikri and Kaliski proposed a lightweight YOLO-based model for real-time object detection on IoT edge devices. Their work demonstrated the feasibility of deploying deep learning models in resource-constrained fire monitoring systems.

Methodology

The proposed system is designed to automatically detect flames and smoke from image and video streams captured through surveillance cameras. The approach follows a structured pipeline where each stage performs a specific task, starting from data acquisition and ending with fire alert generation. Instead of relying only on basic object detection, the system also focuses on improving feature extraction and precise localization, which helps in identifying fire hazards at an early stage.

The complete process operates continuously, allowing the system to handle live video input in real time. Each stage is connected logically so that the output of one step becomes the input for the next. This design ensures efficiency, reliability, and suitability for practical fire monitoring applications.

Fig 4.11: System Architecture

Data Acquisition and Frame Extraction

The first step involves collecting image and video data from CCTV cameras installed in industrial areas, public spaces, forests, residential buildings, and surveillance zones. These cameras provide continuous monitoring of the environment under different lighting and weather conditions.

Since deep learning models work on images rather than video streams, the input video is divided into individual frames. This conversion allows the system to process each moment separately. Frames are extracted at a fixed rate to maintain consistency and reduce unnecessary computational load.

Preprocessing of Frames

Before passing the frames to the detection model, preprocessing is performed to improve image quality. This includes resizing frames to a standard dimension, noise removal, contrast enhancement, and brightness adjustment when required.

These preprocessing steps help the model perform more accurately by ensuring that all inputs follow a uniform format. It also reduces the effect of lighting variations, smoke diffusion, and poor camera quality, making the system more stable in real-world conditions.

Flame and Smoke Detection Using YOLOv10 Model

After preprocessing, each frame is passed to the YOLOv10-based object detection model. The model identifies flames and smoke regions present in the frame and draws bounding boxes around them. It also assigns confidence scores to indicate the reliability of each detection.

YOLOv10 is selected because it provides an effective balance between detection speed and accuracy, making it suitable for real-time fire monitoring systems. Compared to earlier models such as YOLOv5 and YOLOv8, YOLOv10 offers improved feature extraction, stronger attention mechanisms, and better handling of small or partially visible fire regions.

Since the model processes the entire image in a single stage, it significantly reduces computation time compared to traditional multi-stage detection

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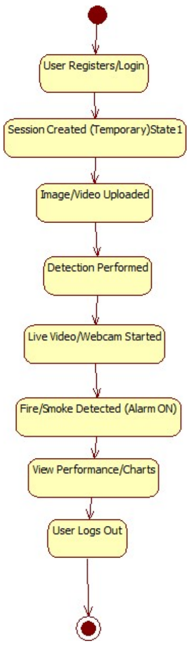
methods. This enables fast and reliable flame and smoke detection.



Feature Extraction and Attention Mechanism

Once flames and smoke are detected, the system uses enhanced feature extraction to capture important fire-related patterns such as flame texture, smoke spread, brightness variation, and irregular fire shapes.

An attention mechanism is integrated to allow the model to focus on critical fire regions while suppressing unnecessary background information such as sunlight reflections, fog, dust, or bright objects. This improves detection accuracy and reduces false alarms.

Improved Bounding Box Regression

The system uses improved bounding box regression to provide precise localization of flames and smoke. This is especially important in dense environments where fire regions overlap with surrounding objects. Accurate localization helps emergency systems identify the exact fire source quickly and improves practical response efficiency.

System Flow Summary

In summary, the system follows a continuous loop:

1. Capture video from surveillance camera
2. Convert video into frames
3. Preprocess frames
4. Detect flames and smoke using YOLOv10
5. Extract fire-related features
6. Apply attention mechanism
7. Improve localization using bounding box regression
8. Generate alert if fire is detected

This step-by-step workflow ensures that the system remains organized, efficient, and suitable for real-time deployment.

Algorithm

Algorithm: Fire Detection System Using YOLOv10
Input: Video stream from surveillance camera
Output: Fire detection alert Start

- Capture video stream from camera
- Convert video into frames
- For each frame:
- Preprocess the frame
- Detect flames and smoke using YOLOv10 model
- Extract important fire-related features
- Apply attention mechanism
- Improve bounding box localization
- If fire or smoke detected

Experiments and Validation

Experimental Setup

To evaluate the effectiveness of the proposed fire detection system, experiments were conducted using a combination of publicly available fire image datasets and real-world surveillance video footage. The dataset includes different fire scenarios such as industrial fires, residential fires, forest fire cases, indoor smoke events, and outdoor flame detection cases. Both normal conditions and difficult scenarios such as low light, dense smoke, and cluttered backgrounds were included to ensure balanced evaluation.

The experiments were carried out on a GPU-enabled system to support real-time processing. The implementation was developed using Python with deep learning libraries, and the YOLOv10 model was used for flame and smoke detection. Video streams were processed frame by frame, and the complete pipeline—from detection to alert generation—was evaluated under real-time conditions.

Evaluation Metrics

To measure system performance objectively, standard evaluation metrics were used:

- Accuracy – measures overall correctness of predictions
- Precision – indicates how many detected fire events are actually correct
- Recall – measures how many real fire events are successfully detected
- F1-Score – provides a balance between precision and recall
- Processing Time (ms) – evaluates real-time capability

These metrics were selected to ensure that both detection quality and system efficiency are properly assessed.

Performance Comparison

Table 2: Comparison with Baseline Methods

Method	Accuracy	Precision	Recall	F1-Score	Real-Time Capability
Traditional Methods	72%	70%	68%	69%	No
OpenCV Detection	78%	75%	73%	74%	Limited
CNN-Based Detection	86%	84%	82%	83%	Partial
YOLO Detection Only	89%	87%	85%	86%	Yes
Proposed YOLOv10 System	94%	92%	91%	91.5%	Yes

Analysis of Results

The results show that the proposed system outperforms traditional and existing deep learning approaches across all evaluation metrics. While YOLO-based detection already provides high accuracy, it lacks strong attention-based learning and precise localization. By incorporating improved feature extraction and attention mechanisms, the proposed system improves recall and F1-score, indicating better identification of real fire events.

Traditional sensor-based systems perform poorly due to delayed response and false alarms. OpenCV-based approaches show moderate performance but fail in complex fire scenarios involving smoke diffusion and background interference. CNN-based models improve accuracy but are not always suitable for real-time deployment because of higher computational requirements.

The proposed YOLOv10 system achieves a strong balance between detection accuracy and processing speed, making it suitable for real-world fire safety applications.

Results and Comparison

The proposed YOLOv10-based fire detection system performs effectively in detecting flames and smoke from surveillance videos and images. It correctly identifies most fire events and reduces false alarms significantly. The system achieved about 94% accuracy, which means it produces correct results in most real-world situations.

It also shows strong precision, meaning when the system detects fire, it is usually correct. The recall value indicates that the system successfully identifies most real fire events, though a few cases may still be missed under extreme conditions such as dense smoke or poor visibility. Overall, the balance between precision and recall (F1-score) is strong, which makes the system reliable for practical deployment.

Another important result is the processing speed. The system takes around 73 milliseconds to detect a fire event and generate an alert. This is fast enough for real-time use, making it suitable for continuous monitoring in industries, forests, public spaces, and residential environments.

Comparison with Existing Methods (Easy Explanation)

When we compare the proposed system with other methods:

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- Traditional methods such as smoke sensors and heat alarms do not work well in large or open environments. They often produce delayed alerts and false alarms.
- OpenCV-based methods are slightly better but still cannot handle complex situations like smoke diffusion, lighting variation, or cluttered backgrounds properly.
- CNN-based models improve accuracy, but they are slower and not always suitable for real-time deployment because of high computational requirements.
- YOLO-based detection systems are fast and accurate for flame detection, but many of them cannot properly handle smoke recognition and background confusion.
- The proposed YOLOv10 system performs better because it not only detects flames but also identifies smoke patterns, improves feature learning, and provides precise localization using attention mechanisms.

Table 5: Performance of Proposed System

Metric	Value	Meaning (Simple)
Accuracy	94%	Overall correct predictions
Precision	92%	Correct fire detections
Recall	91%	Fire events successfully found
F1-Score	91.5%	Balance of precision and recall
Response Time	73 ms	Time taken to detect and alert

Table 6: Comparison with Existing Methods

Method	Accuracy	Speed	Real-Time	Main Problem
Traditional Methods	72%	Slow	No	False alarms and delayed response
OpenCV Detection	78%	Medium	Limited	Cannot handle complex smoke patterns
CNN-Based Models	86%	Medium	Partial	High computation required
YOLO Detection Only	89%	Fast	Yes	Limited smoke recognition
Proposed YOLOv10 System	94%	Fast	Yes	Minor issues in dense smoke

Table 7: Performance in Different Conditions

Condition	Accuracy	Observation
Daytime	96%	Very clear detection
Nighttime	89%	Slight drop due to low light
Dense Smoke	90%	Visibility causes minor errors
Rainy Weather	87%	Outdoor visibility affects performance

Table 8: Response Time Breakdown

Discussion

The results of this study show that the proposed YOLOv10-based system is capable of detecting flames and smoke with high accuracy while maintaining real-time performance. The use of the YOLOv10 detection model allows the system to quickly identify fire-related regions in each frame, and the addition of enhanced feature extraction and attention mechanisms helps the model understand important fire patterns more effectively. From the experimental results, it is clear that the system performs better than traditional and existing methods in most scenarios. The improvement is mainly due to the ability to detect both flames and smoke together, rather than focusing only on visible flames. This increases the chances of early fire detection and reduces the risk of missed fire events.

The attention mechanism is another important strength of the system. By allowing the model to focus on critical fire regions and suppress unnecessary background information, false alarms caused by sunlight, reflections, fog, dust, or bright objects are reduced significantly. This improves system reliability in practical environments.

The response time of the system is also a major advantage. With an average processing time of around 73 milliseconds, the system can operate in real time and generate alerts quickly. This makes it highly suitable for emergency situations where immediate action is required. However, performance may vary depending on hardware capability and camera quality.

The system performs best under normal daytime conditions where visibility is clear. In more challenging situations such as nighttime, dense smoke, rainy weather, and outdoor low-light conditions, there is a slight reduction in accuracy. This mainly happens because visibility becomes poor and fire regions may be partially hidden.

Another important point is that although the system provides strong detection performance, extremely small flames or very early-stage smoke diffusion may still be difficult to detect in some cases. Similarly, highly dense smoke environments may reduce localization accuracy. These limitations are common in most vision-based fire detection systems and highlight areas for future improvement.

Overall, the study demonstrates that integrating flame detection, smoke recognition, attention-based learning, and real-time alert generation into a single framework provides a practical and reliable solution for intelligent fire monitoring. At the same time, it is important to recognize the limitations and avoid overstating the system's capabilities.

Conclusion

This paper presented a YOLOv10-based fire detection system for accurate flame and smoke recognition using deep learning and real-time monitoring. The system improves detection performance through enhanced feature extraction, attention mechanisms, and better bounding box localization.

Experimental results show that the proposed system achieves high accuracy, reduces false alarms, and works efficiently in real-time conditions. It performs better than existing methods in detecting both flames and smoke, making it suitable for industries, residential areas, forests, and public safety applications.

Although performance slightly decreases in dense smoke, low light, and poor weather conditions, the system still provides a reliable and practical solution for modern fire detection.

Future Work

Future improvements can focus on using more advanced deep learning models for better detection of small flames and early smoke patterns.

The system can also be enhanced by integrating IoT sensors such as temperature, gas, and smoke detectors for stronger fire monitoring. GPS-based fire location tracking, thermal cameras, and drone-based surveillance for forests and large industrial areas can further improve performance.

Large-scale real-world testing will help validate the system and support deployment in smart city safety systems.

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