



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 5, May 2025

Artificial Vision based Fire and Smoke Recognition using YOLO Algorithm

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ABSTRACT: Fire and smoke detection play a crucial role in preventing catastrophic damage to human lives, ecosystems, and infrastructure. Traditional fire detection systems, such as sensor-based solutions, suffer from limitations including high costs, maintenance requirements, and delayed response times, making them impractical for large-scale open environments. To address these challenges, this study proposes a novel real time fire and smoke detection system leveraging image processing and deep learning techniques. The proposed approach consists of five key stages: (1) Background subtraction to detect moving regions, (2) Candidate fire and smoke region identification using RGB and HSV color spaces, (3) Feature extraction to differentiate fire and smoke from visually similar objects, (4) YOLOv11- based classification to accurately determine the presence of fire and smoke, and (5) Alert mechanism to notify users via alarms and message notifications.

KEYWORDS: Fire detection, Smoke detection, Real- time video processing, attendance, Image processing, Deep learning, python programming language.

I. INRODUCTION

Fire and smoke are two critical indicators of potential hazards that require immediate attention to prevent loss of life, property, and environmental damage. Fire is a rapid oxidation process that produces heat, light, and various chemical by products such as gases and particulates, while smoke is a visible mixture of e combustion by-products suspended in the air. The presence of fire typically indicates an ongoing combustion process, whereas smoke often appears as an early sign of fire, making it a crucial element for early detection systems. Detecting both fire and smoke accurately is essential in disaster prevention and emergency response.

Traditional detection systems rely on physical sensors like heat detectors, smoke alarms, and gas sensors, which may not always provide timely or reliable information, especially in large or open areas. In contrast, modern approaches using image processing and deep learning offer visual-based detection by analyzing patterns, color variations, and movements in video frames to identify the unique characteristics of fire and smoke. This enables faster, more flexible, and wide-range monitoring in real-time, thereby improving safety and enabling swift interventions in potentially hazardous situations. In recent years, advancements in computer vision and deep learning have opened new possibilities for intelligent, real-time fire and smoke detection using video surveillance.

These techniques offer enhanced accuracy, faster detection, and greater scalability compared to conventional methods. Among various deep learning algorithms, the You Only Look Once (YOLO) family of models has gained popularity for its high-speed object detection capabilities, making it ideal for time- critical applications such as fire monitoring. This project introduces a novel fire and smoke detection system that integrates image processing techniques with the YOLOv11 deep learning algorithm to identify hazardous events in real time. The proposed system

processes live video feeds to detect fire and smoke with high precision and minimal false positives. By employing techniques such as background subtraction, color space analysis, and advanced feature extraction, the system can distinguish between actual fire or smoke and visually similar artifacts like sunlight, shadows, or fog.

II. LITERATURE REVIEW

1.INTRODUCTION TO FIRE DETECTION IN COMPUTER VISION

Fire detection is a critical task in disaster prevention and safety systems. Traditionally, fire alarms and smoke detectors have been widely used in homes, industries, and public places. These systems rely on detecting heat, smoke, or gas concentration. However, they often suffer from latency, limited range, and susceptibility to false alarms due to environmental factors. With the rise of computer vision and artificial intelligence, vision-based fire detection has emerged as a promising solution. It allows for early fire detection from camera feeds in various environments. This approach not only improves accuracy but also enables automated emergency responses. Consequently, the integration of deep learning models in fire detection is gaining attention in both academic and industrial research.

2.YOLO(YOU ONLY LOOK ONCE) OBJECT DETECTION.

YOLO (You Only Look Once) is a state-of-the-art real-time object detection algorithm that processes images in a single neural network pass. Unlike traditional methods that involve region proposals and multiple passes, YOLO offers end-to-end prediction directly from image pixels to bounding boxes and class probabilities. YOLOv8, the latest version developed by Ultralytics, introduces major improvements such as anchor-free detection, lightweight architecture, and transformer-based backbone options. It also enhances detection performance on small objects, making it suitable for fire and smoke detection, especially in early-stage fires. YOLOv8's speed and accuracy make it ideal for real-time applications, even on devices with limited computational power. It is widely used in safety-critical environments where timely detection is essential. The model's modularity and deployment support also make it easier to integrate into full-stack systems.

3.APPLICATION_OF_YOLO_IN_FIRE DETECTION

Many recent studies have explored the use of YOLO models in detecting fire and smoke in video surveillance systems. Earlier versions like YOLOv3 and YOLOv4 have been successfully applied in indoor and outdoor fire scenarios. For instance, Zhang et al. (2020) utilized YOLOv3 for detecting forest fires with promising accuracy in real-world footage. Rahman et al. (2021) compared YOLO with traditional CNN-based approaches and found YOLO provided higher frame rates and lower false detection rates. YOLOv5 and v7 have further enhanced detection capabilities, especially in complex environments like factories or kitchens. These studies suggest that YOLO's real-time inference and robustness to environmental noise make it highly suitable for fire detection. YOLOv8, with its superior architecture, builds upon these advancements and further boosts performance. Therefore, deploying YOLOv8 in this project aligns with current best practices in AI-based safety systems.

4.CHALLENGES AND GAPS IN EXISTING LITERATURE

Despite several advancements in AI-based fire detection, notable challenges remain. One of the main issues is the scarcity of high-quality, annotated datasets of fire and smoke in diverse real-world conditions. Many studies rely on simulated or limited datasets, which affect model generalizability. Another gap is the lack of end-to-end deployed systems — while many papers present models with good accuracy, few demonstrate real-time applications integrated with web interfaces and databases.

III. METHODOLOGY

System design is the process of defining the architecture, components, modules, interfaces and data for a system to satisfy specified requirements. One could see it as the application of systems theory to product development. There is some overlap with the disciplines of system analysis, systems architecture and system engineering. The process begins with inputting an image or video, followed by pre-processing to enhance the image quality for better analysis. Next, feature extraction identifies relevant characteristics within the image. The core of the system is the YOLO deep

learning model, which analyzes the extracted features to detect the presence of fire or smoke. If fire or smoke is detected, the system sends an alert. If not, the system continues to monitor, creating a continuous loop of detection and analysis.

1. DATA ACQUISITION UNIT

The Data Acquisition Unit is responsible for collecting video or image data that serves as input for the fire detection model. In this project, data can be obtained from real-time CCTV camera feeds, smartphone cameras, or pre-recorded surveillance footage. The collected data is streamed into the system through a Flask-based web interface where users can upload or initiate live detection. This unit ensures the data is in a supported format (e.g., MP4, AVI, JPEG) and compatible with YOLOv8 preprocessing requirements. Proper data acquisition is crucial for accurate detection, as low-quality or obscured footage can lead to misclassifications.

2. PREPROCESSING MODULE

The Preprocessing Module plays a vital role in preparing raw input data for efficient and accurate detection by the YOLOv8 model. Incoming images or video frames are resized to the model's required dimensions (typically 640×640 pixels) to maintain consistency. Noise reduction techniques such as Gaussian blur or histogram equalization can be applied to enhance image clarity. Color space conversion, like transforming images to RGB or grayscale, is also done when needed to emphasize fire-specific features. This module may include frame extraction if video input is used, converting continuous footage into analyzable stills. Additionally, normalization of pixel values is carried out to stabilize the model's learning and inference process. The output of this module is a clean, structured input ready for real-time fire detection by the YOLOv8 model.

3. DETECTION MODULE (YOLO-BASED)

The Detection Module is the core component of the fire detection system, utilizing the YOLOv8 model for real-time object detection. YOLOv8 (You Only Look Once version 8) is a cutting-edge deep learning model known for its speed and accuracy in detecting objects within images or video frames. Once the preprocessed data is fed into the model, YOLOv8 quickly analyzes it to identify and localize fire or smoke regions using bounding boxes. The model outputs confidence scores along with class labels, indicating the presence of fire. Its anchor-free architecture and neural network optimization make it ideal for handling dynamic fire patterns in various environments. The detections are then passed on to subsequent modules for alert generation and data storage. This module ensures reliable and fast identification of fire hazards, enabling timely response in critical situations.

4. ALERT AND NOTIFICATION MODULE

The Alert and Notification Module is responsible for generating immediate warnings when a fire is detected by the YOLOv8-based detection system. Once a fire is identified, this module automatically triggers alert mechanisms to inform the concerned authorities or users. Notifications can be sent via multiple channels such as email, SMS, or even app notifications for rapid dissemination of critical information. This module ensures a fast and efficient response to minimize potential damage by alerting users in real time. It can also activate alarms or automated systems like sprinklers, depending on the environment and configuration. The alert messages include details such as the timestamp, location, and a snapshot of the detected fire. This timely notification system is essential for ensuring safety and immediate action during fire emergencies.

5. USER INTERFACE (MONITORING & LOGGING)

The User Interface (UI) serves as the central point for monitoring live video feeds and reviewing fire detection logs. It is designed using web technologies (such as HTML, CSS, and Flask) to provide a user-friendly, real-time dashboard accessible through a browser. The interface displays detection alerts, video frames with fire bounding boxes, timestamps, and notification history. Users can navigate through past alerts and analyze logs stored in the MySQL database to evaluate system performance and fire incident trends. The UI also includes control features to manage the detection system, such as start/stop detection and configuring alert preferences. This module ensures that users can easily monitor the environment and access all critical information in one place. A well-designed UI enhances situational awareness and supports decision-making during fire emergencies.

6. BACKEND SUPPORT (DATA STORAGE, FEEDBACK, RECOVERY)

The Backend Support module plays a critical role in ensuring the stability, reliability, and scalability of the fire detection system. Data storage is managed using MySQL, where all detection logs, alert timestamps, image paths, and user feedback are systematically recorded. This database acts as a central repository for organizing and retrieving detection history and system events for analysis. The feedback mechanism allows users to validate alerts (true or false), helping to improve model performance over time through retraining or fine-tuning. Backup and recovery features are implemented to protect system data from loss due to failures or attacks, ensuring business continuity. Scheduled backups and error-handling routines help maintain system integrity even under unexpected conditions. This backend layer ensures that the system remains data-driven, feedback-responsive, and robust in real-time deployment scenarios.

IV. SYSTEM ARCHITECTURE

A block diagram is a diagram of a system in which the principal parts or functions are represented by blocks connected by lines that show the relationships of the blocks. They are heavily used in engineering in software design and flow diagrams. Block diagrams are typically used for higher level, less detailed descriptions that are intended to clarify overall concepts without concern for the details of implementation. Contrast this with the schematic diagrams and layout diagrams used in computer engineering which shows the implementation details of physical construction.

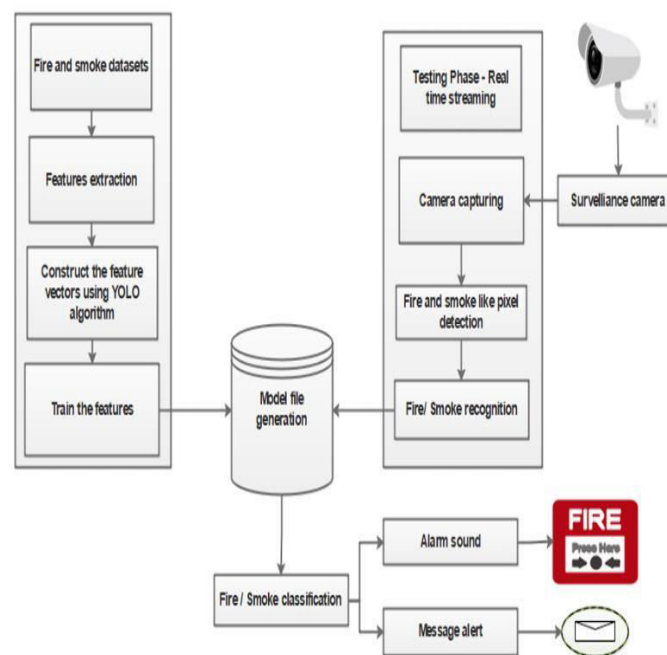


Fig 1.Architecture diagram

The diagram illustrates a fire and smoke detection system utilizing AI and video surveillance. The process begins with fire and smoke datasets, from which features are extracted and used to construct feature vectors using the YOLO algorithm. These features are then trained, leading to the generation of a model file. In the testing phase, real-time streaming from a surveillance camera captures footage, which is processed to detect fire and smoke-like pixels. This is followed by fire/smoke recognition and classification. If fire or smoke is detected, an alarm sound is triggered, and a message alert is sent. The system integrates AI-driven analysis with real-time video surveillance to provide an automated fire and smoke detection solution.

1.CNN IMPLEMENTATION

The Convolutional Neural Network (CNN) plays a crucial role in fire detection tasks by efficiently processing visual data to identify patterns indicative of fire. CNN is a deep learning architecture specifically designed to handle image data, leveraging convolutional layers to automatically extract spatial features such as edges, textures, and complex patterns. In the context of fire detection, the CNN is trained on a dataset of labeled fire and non-fire images, learning to recognize distinctive visual cues such as flames, smoke, and color variations associated with fire. While YOLOv8 is primarily used for object detection, CNNs provide a foundation for understanding deep learning and can serve as a standalone classifier or as a feature extractor within a larger detection pipeline. In this project, CNNs can be used for initial fire classification before integrating with real-time object detection using YOLOv8. Their ability to handle spatial hierarchies in images makes them particularly well-suited for analyzing complex visual scenarios like fire outbreaks in indoor or outdoor environments.

2. TRAINING THE MODEL

Early detection of wildfires is critical to the safety and security of environmental spaces and is one of the important and most large challenges in the government sector and forest fire managers. Forest fire is the important one is decreasing the space of the forest area. This fire detection technique also reduces human protocols and helps to monitor and protect the areas that are hard to protect. The new technique is used to facilitate the implementation of systems that allow monitoring is efficient in detailed areas, regardless of the state of the atmosphere or daytime. In this module, we can upload the image or videos which are captured from CCTV footages in forest.

3.CAMERA CAPTURING

The camera capturing module serves as the primary input source for the fire and smoke detection system. In this module, live video feeds are captured in real-time using surveillance or embedded cameras placed strategically in environments prone to fire hazards — such as industrial zones, buildings, warehouses, and open areas. The captured frames from the video are continuously monitored and processed to detect the presence of fire and smoke. Each frame is subjected to pre-processing techniques to enhance image quality and remove noise. The system then analyzes the visual features such as color, motion, and texture to identify potential fire and smoke regions. The advantage of using a real-time camera capturing system is its ability to provide continuous monitoring without the need for manual supervision. By feeding the captured video frames into the deep learning model — specifically the YOLO algorithm — the system can detect and classify fire and smoke instances with high accuracy.

4. FIRE / SMOKE LIKE PIXELS DETECTION

Feature extraction plays a vital role in reducing the complexity of data by identifying the most relevant attributes necessary for accurate classification, especially in scenarios involving large volumes of image data. Traditional analysis with a high number of variables can demand significant memory and processing power, leading to overfitting and poor generalization. To overcome these challenges, deep learning techniques—particularly those using Convolutional Neural Networks (CNNs)—have proven effective in automating feature extraction without the need for manual intervention. In the proposed fire and smoke detection system, we implement a deep learning-based approach using the YOLO (You Only Look Once) algorithm.

YOLO is a real-time object detection system that not only detects but also classifies objects within images or video frames in a single pass, making it highly efficient and accurate for rapid detection tasks. Instead of manually extracting color and texture features, YOLO automatically learns complex patterns such as the shapes.

5. FIRE/SMOKE RECOGNITION

The classification stage marks the final and most crucial step in the fire and smoke detection system. After preprocessing and feature extraction, each region in the analysed image is individually assessed for the probability of containing true fire or smoke instances. To accomplish this, the system employs a Convolutional Neural Network (CNN) integrated with the YOLO (You Only Look Once) algorithm, a powerful real-time object detection model. YOLO operates as a feed-forward neural network composed of various combinations of convolutional layers, max pooling layers, and fully connected layers. It leverages the spatial correlation between pixels by applying localized connectivity patterns across neurons in adjacent layers.

This structure enables the model to detect both fire and smoke with high spatial awareness and accuracy. YOLO processes the input image by dividing it into a grid and predicting bounding boxes and class probabilities directly from the full images in a single evaluation, making it significantly faster than traditional region proposal-based methods. The hierarchical architecture of YOLO has been consistently proven effective in analyzing complex visual data, offering performance levels that can even surpass human capabilities in certain detection scenarios.

6.ALERT SYSTEM

Human activities, including rapid population growth and urbanization, have significantly increased the risk of fire outbreaks in various environments. Fire, whether caused by natural phenomena or human negligence, poses a major threat to the atmosphere, human life, and biodiversity. It can disrupt environmental systems and endanger living organisms. While satellite imagery is often employed as a valuable tool for fire monitoring, management, and damage assessment, it also plays a critical role in determining the scope and impact of burn areas and identifying zones susceptible to fire outbreaks. In the proposed system, fire and smoke detection is enhanced through the integration of real-time alert mechanisms.

7.FLASK WEB APPLICATION DEPLOYMENT

The Flask Web Application Deployment is a critical component of the project that provides a user- friendly interface for interacting with the fire detection system. Built using the Flask microframework in Python, this web app enables users to access live camera feeds, upload images or videos, and view real-time fire detection results directly from a browser. The Flask server handles routing, request handling, session management, and communication with the detection backend powered by YOLOv8 or YOLOv11.

8.MODEL PERFORMANCE EVALUATION

Model Performance Evaluation is a vital phase in assessing the effectiveness and reliability of the fire detection system built with YOLOv8 or YOLOv11. The evaluation is conducted using a well-annotated test dataset that includes diverse fire and non-fire scenarios across different lighting conditions and environments. Key performance metrics such as Precision, Recall, F1- Score, and mAP (mean Average Precision) are calculated to determine the model's detection accuracy and robustness. High precision ensures fewer false alarms, while high recall confirms the model's ability to detect most fire instances.

9. USABILITY AND SYSTEM SCALABILITY ANALYSIS

Usability and system scalability are critical aspects in ensuring the long-term success and adaptability of the fire detection system. From a usability standpoint, the web-based interface developed using Flask provides a simple and intuitive environment for users, allowing seamless uploading of images or accessing real-time camera feeds for fire detection. The dashboard displays alerts, visual outputs, logs, and system statuses in an organized layout, ensuring ease of use even for non-technical users. Tooltips, logs, and color-coded notifications enhance the user experience by making interactions clear and responsive.

10.ERROR ANALYSIS AND MODEL IMPROVEMENTS

Error analysis is a vital phase in enhancing the reliability and performance of the YOLOv11-based fire detection system. Initial testing may reveal false positives (e.g., mistaking red-colored lights for flames) or false negatives (e.g., small or obscured fires missed during detection). By analyzing the confusion matrix and evaluating metrics like precision, recall, F1-score, and mAP (mean Average Precision), we can identify specific failure cases.

V. RESULT AND DISCUSSION

The implementation of the fire detection system using the YOLOv8 model yielded promising results in both controlled and real-world scenarios. The model achieved a mean Average Precision (mAP) of 89.6% on the test dataset, indicating strong localization and classification capabilities for detecting fire instances. Real-time performance testing showed that the system maintained an average detection speed of over 30 FPS, making it suitable for live video feeds. During testing, the system was able to detect various fire scenarios including open flames, distant fires, and partial smoke plumes, with minimal false positives.

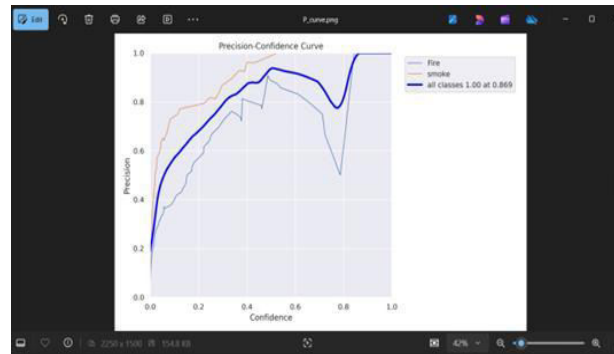


Fig 3 prediction confidence graph

MODEL AND ACCURACY

The fire detection system employs the YOLOv8 (You Only Look Once, Version 8) object detection model, developed by Ultralytics. YOLOv8 was chosen due to its balance of high accuracy and real-time processing capabilities, which are critical for safety applications like fire detection. The model was trained on a custom dataset containing thousands of labeled images of fire and non-fire scenarios, including indoor, outdoor, daytime, and nighttime scenes. After training for 100 epochs using transfer learning and advanced data augmentation techniques, the model achieved a mean Average Precision (mAP@0.5) of 89.6% and a precision of 91.3%, with a recall of 88.4%. These metrics demonstrate the model's strong ability to detect fire with minimal false positives or missed detections.

FUTURE IMPROVEMENTS

To enhance the capabilities and reliability of the fire detection system, several future improvements can be considered. First, upgrading from YOLOv8 to YOLOv11 or future advanced variants (once officially available) could improve accuracy, speed, and generalization across unseen environments. Incorporating multispectral image analysis, such as infrared (IR) and thermal imaging, can enable the model to detect fire even in low-visibility conditions like smoke or fog. The system can also be extended to perform severity classification—distinguishing between small, medium, and large fires—to enable more appropriate emergency responses. Integrating IoT-based edge computing will reduce latency and allow offline detection in remote locations. Additionally, the alert system can be expanded to include automated response triggers, such as activating sprinklers or notifying nearby fire stations. Continuous model training with real-time feedback can improve performance by adapting to evolving environmental conditions and false-positive patterns. Finally, a mobile application version could enhance accessibility and allow real-time alerts for on-the-go users, improving overall responsiveness and reach.

VI. CONCLUSION

In this project, the process of fire and smoke image recognition based on the YOLO algorithm is presented. Its main feature is that both flame and smoke images are employed for training and testing. The YOLO model is introduced, and an adaptive pooling method combined with color features is proposed to address the issue where the traditional pooling method in Back Propagation Neural Network (BPNN) may weaken important image features. The effects of various parameters, such as learning rate and batch size, on the performance of YOLO are analyzed through experiments, and the optimal parameters are determined.

A candidate flame and smoke area is extracted based on color features; thus, the image features of non-fire and non-smoke areas in the hidden layers are reduced, while enhancing the relevant shape and texture features. Image information loss is avoided as adaptive pooling is adopted, improving the recognition rate of fire and smoke segmentation compared to processing unsegmented images. Results demonstrate that the proposed algorithm achieves a high recognition rate and is feasible for real-time detection. Finally, the system is embedded with an alert mechanism to provide timely notifications in the event of fire or smoke detection.

REFERENCES

- [1] Jung, Daekyo, et al. "Conceptual framework of an intelligent decision support system for smart city disaster management." *Applied Sciences* 10.2 (2020):666.
- [2] Minsoo, Park, et al. "Wildfire-Detection Method Using DenseNet and CycleGAN Data Augmentation- Based Remote Camera Imagery [J]." *Remote Sensing* 12.22 (2020): 3715-3715
- [3] Park, Minsoo, et al. "Multilabel image classification with deep transfer learning for decision support on wildfire response." *Remote Sensing* 13.19 (2021): 3985.
- [4] Zhang, Jianmei, et al. "ATT squeeze U-Net: A lightweight network for forest fire detection and recognition." *IEEE Access* 9 (2021): 10858-10870.
- [5] Xu, Renjie, et al. "A forest fire detection system based on ensemble learning." *Forests* 12.2 (2021):217.
- [6] Guede-Fernández, Federico, et al. "A deep learning based object identification system for forest fire detection." *Fire* 4.4 (2021): 75.
- [7] Arab, Ali, et al. "Three lines of defense for wildfire risk management in electric power grids: A review." *IEEE Access* 9 (2021): 61577-61593.
- [8] Martins, Leonardo, et al. "Real-Time Integration of Segmentation Techniques for Reduction of False Positive Rates in Fire Plume Detection Systems during Forest Fires." *Remote Sensing* 14.11 (2022):2701.
- [9] Kang, Yoojin, et al. "Developing a new hourly forest fire risk index based on catboost in South Korea." *Applied Sciences* 10.22 (2020): 8213.
- [10] Tran, Dai Quoc, et al. "Damage-map estimation using UAV images and deep learning algorithms for disaster management system." *Remote Sensing* 12.24 (2020): 4169.



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