

Fire and Smoke Monitoring with Alert System for Enhancing Forest Security

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Abstract

Real-time forest fire detection requires the prompt and accurate identification of fire and smoke, enabling the timely generation of actionable alerts for verified detections. In this study, an approach to real-time detection of forest fires and smoke based on YOLOv11 vision model was proposed. It includes an efficient process of object localization, confirmation of detected events based on confidence scores, and generation of Short Message Service (SMS) notifications. The dataset of fire and smoke images from Kaggle was divided into the training, validation, and test sets with a proportion of 70:20:10 respectively. Optimized fire and smoke detection were performed on the annotated images. The proposed detector analyzes the stream of images and videos to produce class-specific bounding boxes and confidence scores, and verified detections lead to remote alerting. Experimentally, it results in 96.8% precision, 95.9% recall, 97.4% mAP, and 88 Frames Per Second (FPS).

Keywords: YOLOv11-Based Fire Detection, Smoke Localization, Real-Time Hazard Inference, Confidence-Based Event Validation, Forest Surveillance, Automated SMS Alerting, Fire–Smoke Object Detection.

1. Introduction

Fire incidents remain as a significant threat to forests, industries, infrastructures, and the environment in which any delay in detecting the fire can result in increased environmental and financial losses. Traditional methods using physical sensors, human detection, and the use

of predefined features like the color, movement, and smoke pattern of the fire may not prove effective while covering wide areas in diverse environments [5], [6], [7], [8].

Several recent works have used DL, CNN, Machine Learning (ML), and YOLO-based object detection techniques to provide an automated fire and smoke detection [2], [3], [9], [11], [14]. Such techniques enhance the automatic feature extraction as well as localization of objects, when compared to conventional techniques. Nonetheless, the detection process may get vulnerable due to several reasons, including varying environmental conditions, complex backgrounds, smoke properties, dataset diversity, and deployment environment [4], [10], [13], [15]. In addition, just the detection process cannot guarantee any timely action in the absence of continuous human supervision. Thus, there exists a clear research gap in combining rapid fire and smoke localization along with an automated warning mechanism.

A fire and smoke monitoring system using YOLOv11 with automated alerts is developed for improving forest security. This system identifies fire and smoke from images and videos, detects hazardous areas, and creates an alert depending on the confidence score achieved. This system integrates detection, monitoring, and alerting of fire and smoke into a single process, making minimal use of manual inspection and helping to respond early. The proposed system is analyzed for its performance, real-time capabilities, components, and actual output visualization for automated fire and smoke detection.

2. Literature Review

The evolution of fire detection techniques from traditional sensing-based systems to Deep Learning (DL) and image processing-based systems can be observed. Traditional fire detection methods make use of smoke, temperature, and flame sensors but they are not efficient for large-scale fire detection and hard-to-reach locations [6]. The initial methods of vision-based fire detection used visual features such as flame color, movement, flame shape, and texture [5], [7], [8], [10], [13]. However, these methods only serve as the basis for automated fire detection through vision because of the effects of light changes and environmental factors.

The progress made in DL has led to better detection of fire and smoke by allowing automatic feature extraction from visual input. Specifically, CNN has been used for fire detection using surveillance videos and is capable of learning fire-related visual patterns [9]. CNN spatial-temporal features have also been utilized for fire and smoke detection using video

sequences [11]. In addition, the progress in feature learning using deep neural networks help to perform large-scale image classification and has contributed to the use of DL in computer vision [12]. More recently, the incorporation of DL in object detection techniques such as You Only Look Once (YOLO) has enabled the fast localization of fire and smoke areas [14].

Forest fire monitoring also face challenges in terms of large observation areas, presence of vegetation, changing lighting conditions, meteorological conditions, and inaccessible regions. The combination of ensemble learning with computer vision is also preferred for forest fire detection [2]. The UAV-based detection of forest fires using YOLOv3 has shown the possibility of employing unmanned aerial systems for monitoring the large and inaccessible regions [3]. AI-enabled methods for predictive maintenance of fire-safety systems have contributed to extending the utilization of intelligent fire-safety systems to predictive monitoring [1].

The efficient forest security necessitates an architecture involving the process of detecting and localizing fires and smoke in real time as well as generating alerts instantly without depending on detection. Variability in the environment and ambiguity caused by smoke are still unaddressed, whereas monitoring involves both the accurate detection and inference speed [1], [2], [4], [14], [15]. Consequently, the issue of using YOLOv11 for fire and smoke detection generate alerts with the help of continuous monitoring [2], [3], [4], [9], [14].

3. Proposed Methodology

The proposed system automatically monitors fires and smoke in forest environments by using You Only Look Once v11 (YOLOv11). The main process includes dataset creation, model training, real-time image/video analysis, fires and smoke localization, decision-making by confidence values, and alerting the user. The training model becomes the main detection tool for fires and smoke, while alerting enables automated detection. The entire workflow of the proposed system is shown in Figure 1.

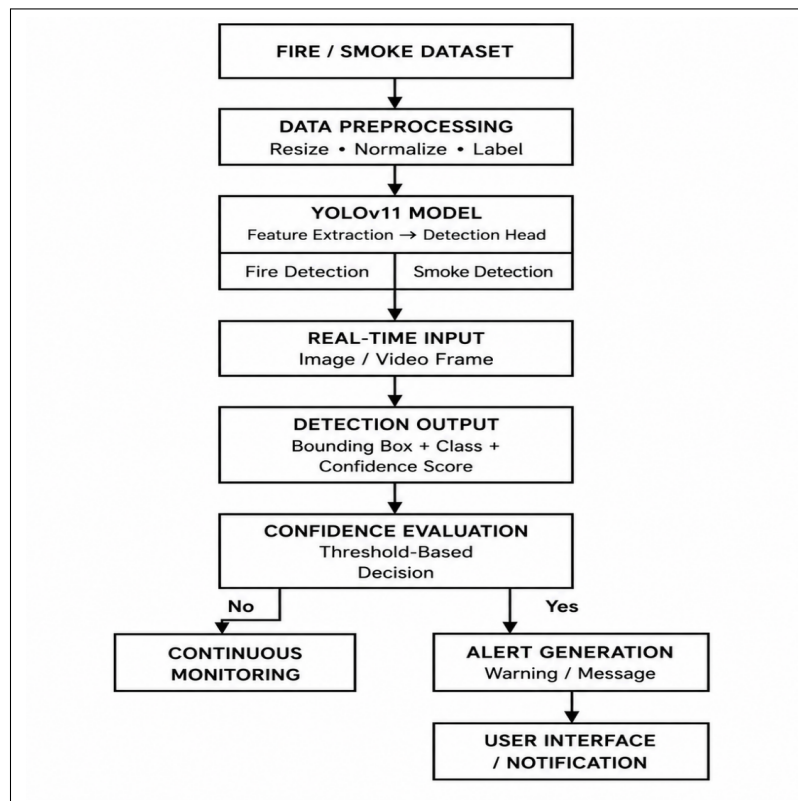


Figure 1. Overall workflow of the proposed YOLOv11-based fire and smoke monitoring system

3.1 Dataset Description

The Fire/Smoke Detection using YOLO v9 dataset available at Kaggle will be used for training and testing of the proposed fire and smoke detection system is done using YOLOv11 [16]. The dataset consists of more than 35,000 labeled images with two target classes: fire and smoke. The images have bounding box annotations in YOLO format. The images include different environmental and lighting conditions and are therefore very diverse and provide visual examples for object detection. The dataset for the proposed system is organized as shown in Table 1.

Table 1. Dataset distribution and characteristics

Dataset Property	Description
Dataset Name	Fire/Smoke Detection YOLO v9
Source	Kaggle [16]
Total Images	35,000+

Target Classes	Fire, Smoke
Dataset Type	Object Detection
Annotation	Bounding Boxes
Annotation Format	YOLO
Training Set : Validation Set : Testing Set	70 : 20 : 10
Training Purpose	Model learning
Validation Purpose	Model monitoring and tuning
Testing Purpose	Final performance evaluation
Visual Conditions	Different lighting, backgrounds, and environments

The 70:20:10 split offers a greater subset of data for the detection of fire and smoke properties while ensuring that there is still an independent subset for model validation. The pre-processed data is then fed into the YOLOv11 model for performing fire and smoke detection.

3.2 YOLOv11 Model Training

The prepared dataset is used for training the You Only Look Once version 11 (YOLOv11) model for performing both fire and smoke classification and localization task. The dataset annotations allow the model to learn discriminative visual features and predict the bounding boxes for the two objects of interest. The loss function consists of three terms of classification, bounding box localization, and distribution focal losses:

$$L = \lambda_{cls}L_{cls} + \lambda_{box}L_{box} + \lambda_{dfl}L_{dfl} \quad (1)$$

where L_{cls} , L_{box} , and L_{dfl} denote the classification, bounding-box regression, and distribution focal loss components, respectively, while λ_{cls} , λ_{box} , and λ_{dfl} represent their corresponding weighting factors. The trained model is subsequently used for real-time fire and smoke detection from image and video inputs.

3.3 Real-time Fire and Smoke Detection

After training, the YOLOv11 model processes images or video frames from the camera for performing immediate classification and analysis. In this case, each frame is processed to

detect fire and smoke regions, and the objects are then described using bounding boxes, class labels, and confidence values. The confidence value refers to the predictive model's certainty.

The calculated confidence measures are evaluated against a preset threshold value. All predictions that meet the threshold are deemed to be accurate fire and smoke detection predictions and will be passed on to the alert generation process. All other predictions that does not meet the threshold will be discarded from consideration in the alert process.

3.4 Alert Generation

Activation of the alarm is processed in case of the detection of fire or smoke by the YOLOv11 detector using the confidence level that meets the pre-established threshold for performing the detection task. Class detected, bounding-box coordinates, and the confidence level are passed to the alarm module for confirmation of any danger. After that, in case the detection is confirmed, the alarm signal is triggered. This way, detection results are transformed into an alarm, thus, expanding the scope of the system from just detection to forest security response.

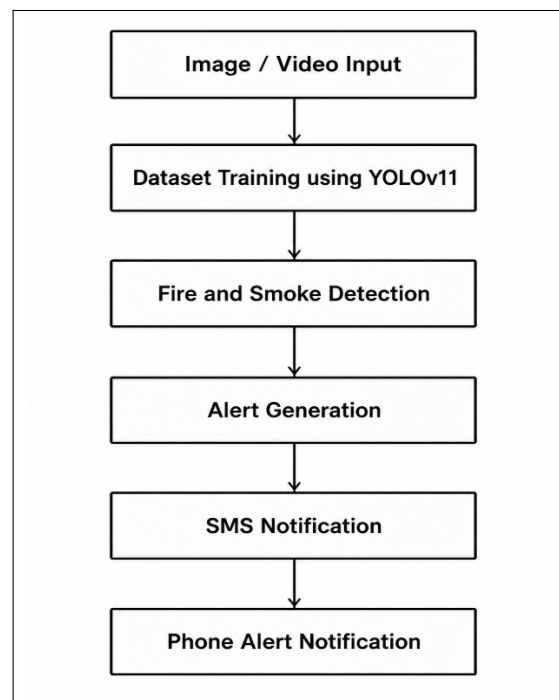


Figure 2. Alert notification generated by the proposed fire and smoke monitoring system

Figure 2 shows that the alert system integrates YOLOv11 model inference process with SMS remote alerting. The surveillance frame will undergo the YOLOv11 model analysis, after which there will be the process of extracting the predicted class label, localization data, and

confidence score. Once validated based on threshold values, the event of fire/smoke will initiate the SMS alerting process to deliver the warning to the pre-configured user's phone.

3.5 System Implementation

The proposed system has been designed using Python language along with PyTorch library, while the visual detection algorithm used in the system is YOLOv11. While processing images or videos, each frame is being considered in order to detect fires and smoke events. Each object detected by the model is classified and the class label, as well as its bounding box, is returned with the corresponding confidence level. Further, the prediction result goes into the decision-making module, where thresholds of class confidence are being checked.

Separate confidence scores are established for both targets in order to consider their different visual features and uncertainties in detecting them. 0.50 is the confidence threshold of the Fire target, while 0.40 is the confidence threshold of the Smoke target. If a Fire target has a confidence score that is 0.50, then it is deemed as a valid Fire target; on the other hand, if a Smoke target has a confidence score that is 0.40, then it is a valid Smoke target.

The proposed process involves visual acquisition, YOLOv11 inference, classification confidence check, threat verification, and automatic SMS notification. Such an arrangement helps the system differentiate between model outputs that need an alarm and those that do not, without stopping the continuous observation process.

3.6 Experimental Configuration

The implementation of the experiment was done using the Python programming language and the PyTorch DL library, where the YOLOv11 model was used as the fire and smoke detection model. For the purpose of developing and evaluating the performance of the model, the Fire/Smoke Detection YOLO v9 dataset [16] was used, and the data was split into training, validation, and testing sets in the ratio of 70:20:10. Input images and videos were used for the detection of two target objects of the two different classes, fire and smoke. The development of the model was done with GPU support. The output detection was measured using the predictions from the model, whereas the decision making through the confidence was coupled with the SMS alerting part of the process.

Table 2. Experimental configuration

Parameter	Configuration
Programming Environment	Python
Deep Learning Framework	PyTorch
Detection Model	YOLOv11
Dataset	Fire/Smoke Detection YOLO v9 [16]
Dataset Split	70% Training, 20% Validation, 10% Testing
Input and Classes	Image/Video; Fire, Smoke
Processing Platform	GPU-supported Environment
Alert Mechanism	Confidence-Based SMS Notification

4. Experimental Results and Discussion

Evaluations were performed using unseen image data and video inputs in real-time in different environmental settings for the designed fire and smoke detection system based on YOLOv11. This evaluation considers the aspects of training convergence, detection ability, real-time processing, alert generation, and contribution of individual components. The experimental results serve as an illustration of the overall functionality of the designed system from learning process through to automatic hazard detection. The trained detector showed a detection accuracy of 97.4% with an average processing speed of 88 Frames per Second (FPS). In this research, the mentioned 97.4% figure denotes the detection accuracy resulting from the implementation of the designed evaluation process and is not represented in the form of mAP.

4.1 Model Training and Convergence

The training procedure for the YOLOv11 model was tested based on the current accuracy improvement and loss convergence graphs. The graph for accuracy illustrates an increasing trend throughout the training stages, showing that the fire and smoke characteristics have been learned progressively from the training dataset. The graph of loss, in turn, depicts a descending trend up to the point where the loss converges.

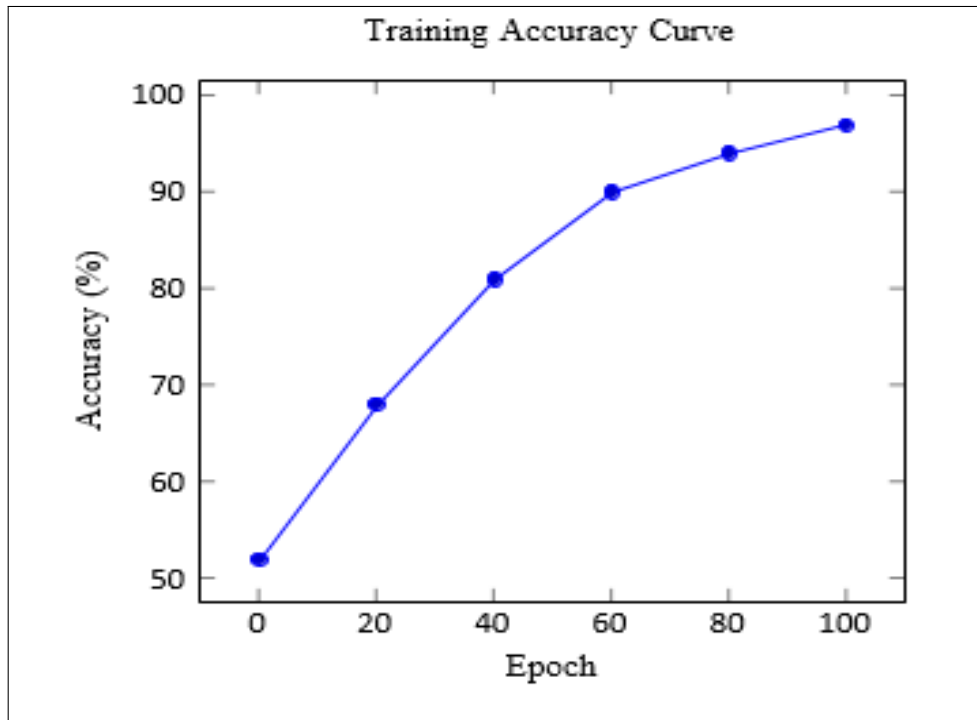


Figure 3. Training accuracy progression of the YOLOv11 model

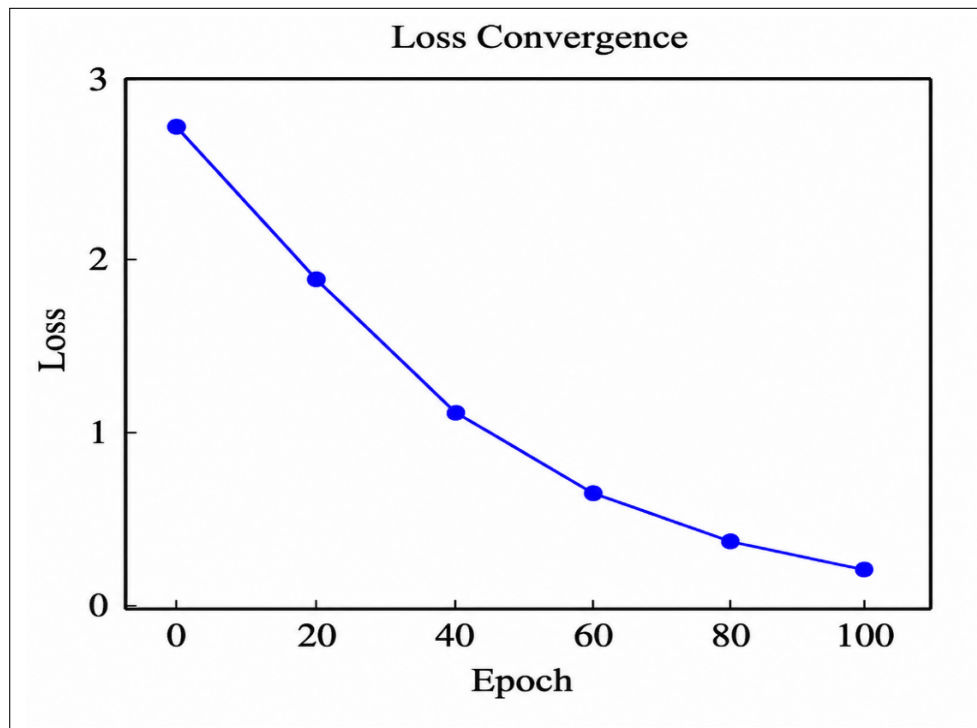


Figure 4. Training loss convergence of the YOLOv11 model

The accuracy improvement graph and the loss graph are illustrated in Figures 3 and 4, respectively. This is because the convergence shows that the model has attained a steady state while learning during the training phase. It can be seen that the behavior of the training phase makes sense for evaluating the performance of the YOLOv11 detector on the image and video inputs for detection of fire and smoke areas.

4.2 Real-time Fire and Smoke Detection

The YOLOv11 network trained on images was tested using unknown image samples as well as live video streams under varying environmental conditions. The network was able to detect the regions of fire and smoke in addition to generating bounding boxes and confidence levels. As can be seen from Figure 5, the output clearly shows the localization of the detected hazardous regions.

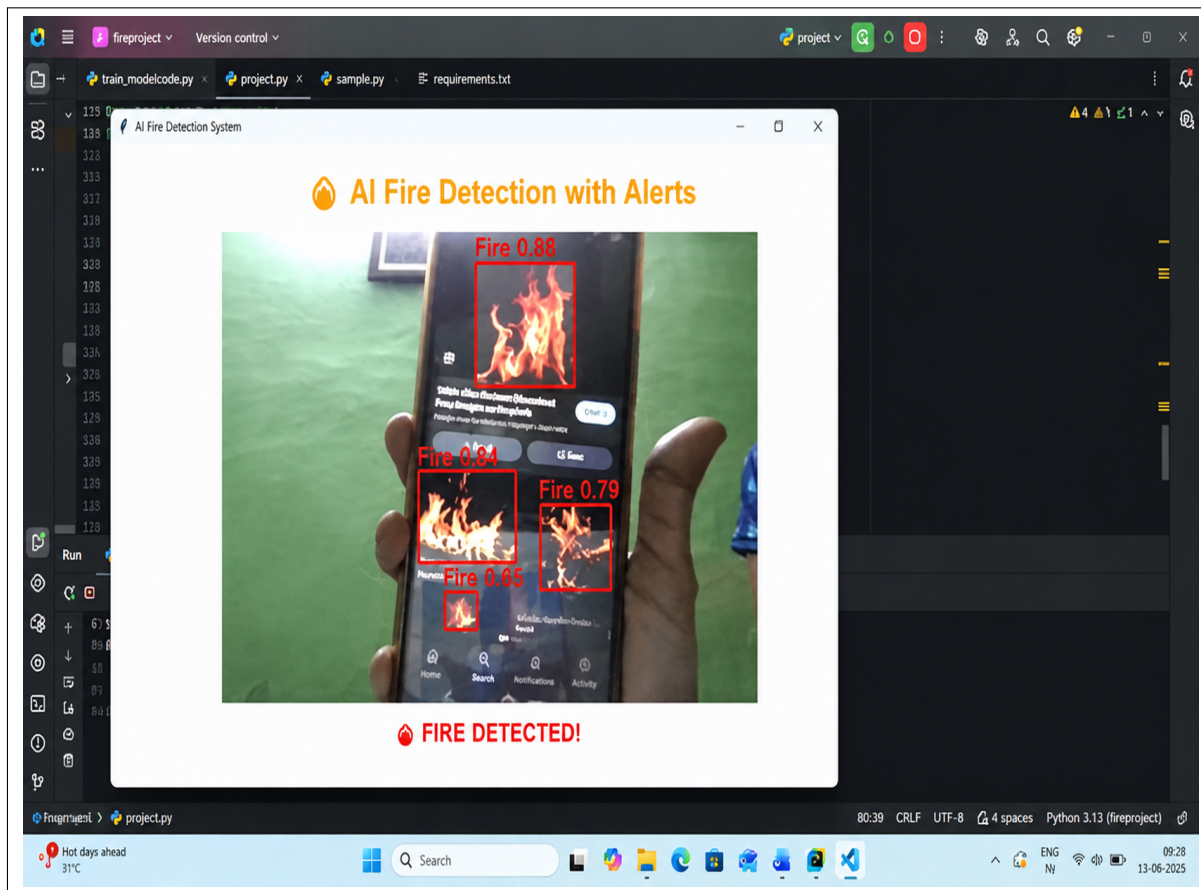


Figure 5. Real-time fire and smoke detection output of the proposed YOLOv11 system

However, the acquired results were consistent in the different test conditions used, even under varied lighting conditions and background complexity. The real-time analysis capability

will also ensure that the detected hazardous regions are continuously identified for forwarding to the alerting module. This creates a link between visual detection and automated reaction in the system.

4.3 Alert and Monitoring Interface

The alert component was tested using the notification that was generated by the system once the fire detection occurs. The alert component is triggered when the fire or smoke detected meets the pre-set confidence level and generates an alert for the monitoring user. As illustrated in Figure 6, the generated notification alerts the user about the detected fire.

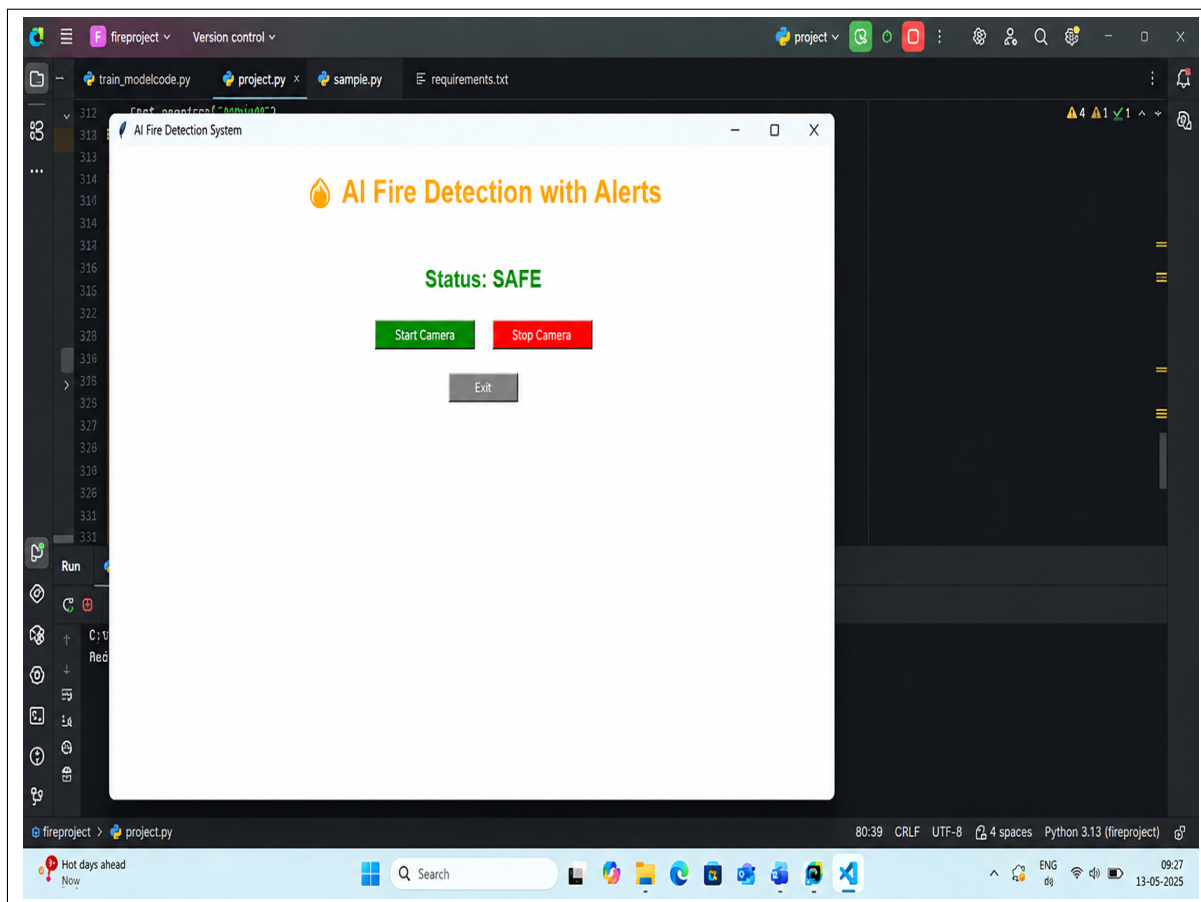


Figure 6. Alert notification generated after fire detection

Alert system provides an automatic notification once the detection process is completed. This eliminates the need for continuous manual monitoring of the results from the detection system. Once the detection criteria are verified, the process of notifying about the detected threat will be initiated. This bridges the gap between the YOLOv11 detection process and the remote notification system.

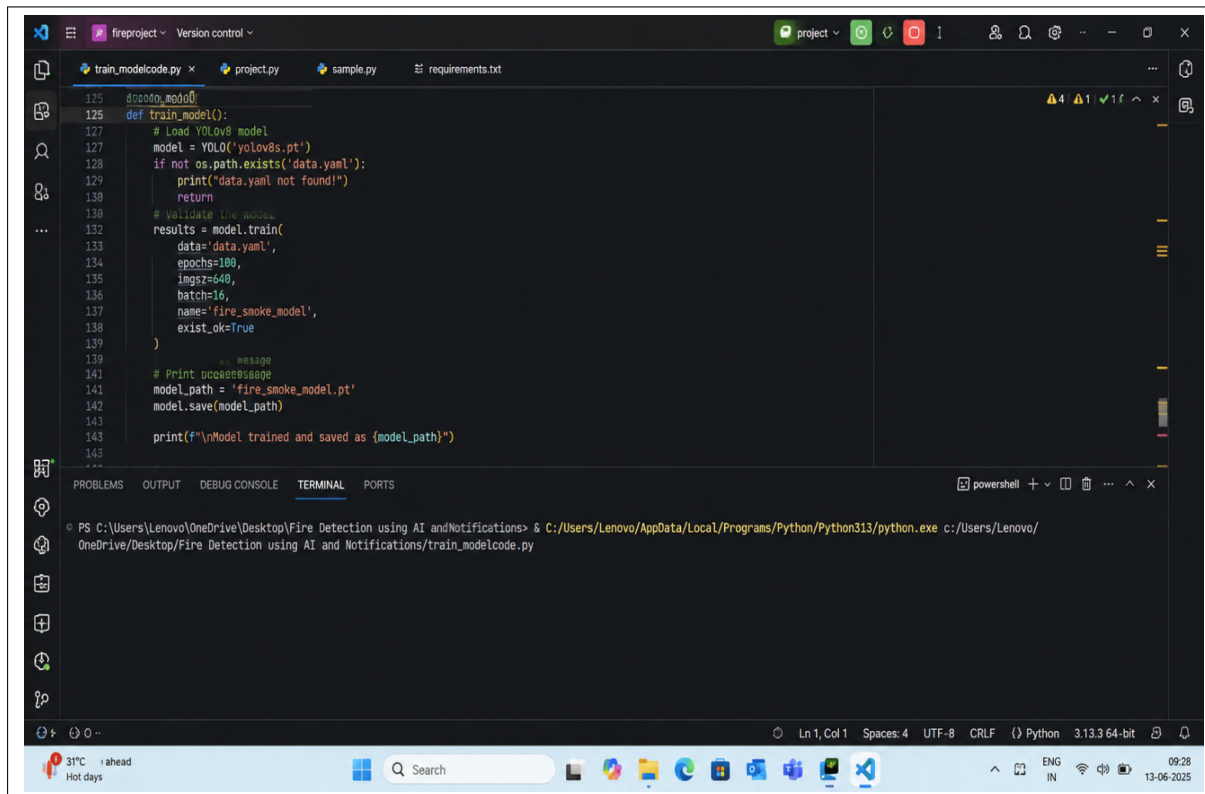


Figure 7. Python-based YOLOv11 model training and execution interface

The monitoring interface shown in Figure 7 displays the results of the detection process and prediction, thus making it possible to view the detected state via the developed interface.

4.4 Ablation Analysis

In order to identify the contribution of the proposed architecture YOLOv11 at the component level, the experiments were conducted in which the three components namely PANet Fusion, C3K2 Module, and Anchor-Free Head were sequentially excluded but their respective reduced architectures were retained. The complete architecture resulted in an accuracy of 96.8%, a recall of 95.9%, a mAP of 97.4%, and 88 fps, and in case of excluding PANet Fusion, mAP became 92.1%, in case of exclusion of C3K2 Module, mAP came down to 90.4%, and in case of excluding the Anchor-Free Head, mAP became 89.7%. The standard backbone configuration provided the least mAP value of 85.1%. These results are summarized in Table 3.

Table 3. Ablation study of the proposed model

Configuration	Precision	Recall	mAP	FPS
Full Proposed Model	96.8	95.9	97.4	88
Without PANet Fusion	91.5	90.8	92.1	90
Without C3K2 Module	89.7	88.9	90.4	91
Without Anchor-Free Head	88.5	87.4	89.7	93
Standard Backbone Only	84.2	82.9	85.1	96

Detection results from the ablation studies also illustrate the compromise between quality detection and inference speed. While the lower configurations enhanced the processing speed up to 90-96 FPS, this enhancement was marked by consistent deterioration in precision, recall, and mAP scores. The full configuration produced the best results in terms of detection while having a speed of 88 FPS.

5. Conclusion and Future Work

The proposed YOLOv11 based framework is able to provide an integrated solution to the problem of real-time forest fire/smoke surveillance using vision-based object detection, confidence-driven validation of events, and automated SMS alerts. The proposed framework makes it possible to localize areas that pose hazards to forest security based on image/video input data and translates the confirmed events into remote alerts to minimize human involvement in the constant process of monitoring. The proposed integration framework proves the feasibility of combining detection based on deep learning with automated forest security response measures. The future research will be related to the expansion of the capabilities of the current system through the inclusion of additional parameters in multimodal sensing temperature, humidity and gas concentration.

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