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Research Paper

Next-Generation Vision Intelligence for Wildfire Smoke Detection Using YOLOv8 Architecture

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Abstract

Wildfires are one of the most destructive natural disasters, causing severe damage to forests, wildlife, human life, and property. Early detection of wildfire smoke is essential to prevent the rapid spread of fire and to enable timely response from disaster management authorities. Conventional fire detection methods such as manual surveillance and basic sensor-based systems often suffer from delayed detection, limited coverage, and high operational costs. This project presents an intelligent wildfire smoke detection system using the advanced deep learning object detection model YOLOv8 (You Only Look Once Version 8). The proposed system is designed to automatically detect smoke from images captured through ground-based cameras and surveillance systems. The YOLOv8 model is trained on a diverse dataset containing wildfire smoke images under different environmental and lighting conditions to improve detection accuracy and robustness. The system architecture consists of image acquisition, preprocessing, model training, smoke detection, and result visualization through a user-friendly Tkinter graphical interface. The trained model identifies smoke regions by generating bounding boxes along with confidence scores, ensuring reliable and real-time detection performance. Experimental results demonstrate that the proposed system achieves high accuracy, improved precision and recall, and reduced false positives compared to traditional image processing methods. The system can be integrated with surveillance cameras and alert mechanisms to provide an efficient early warning solution for forest fire prevention.

Keywords: Wildfire Detection, Smoke Detection, Fire Detection, YOLOv8, Computer Vision, Surveillance Systems.

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1. INTRODUCTION

When wildfires occur, the first thing observed in the air is a massive column of smoke. A reliable smoke alarm is essential for preventing fire-related losses. Rapidly spreading wildfires, exacerbated by climate change, can have far-reaching consequences on human communities, ecosystems, and economies, if not detected or extinguished quickly. Smoke and flame detection are both applicable to wildfire monitoring. Smoke is the first visible indicator of a wildfire. Therefore, an early warning wildfire detection system must be able to detect smoke in natural environments. Smoke from wildfires has the following three primary properties: it is physically present, visually distinct, and dynamic. For a sensor to collect representative samples of smoke, it must be within close proximity of the smoke to detect its physical characteristics. In this study, we primarily focus on the other two properties, visually distinct and dynamic, which are perceptible to a camera. Initially, this section describes the economic issues and the reasons for the wildfires. Second, we analyse the current sensors and methods to detect wildfire smoke. Following this, a deep learning (DL) approach for detecting wildfire smoke is proposed. Fig. 1 illustrates the end-to-end operational flow of a wildfire smoke detection system based on deep learning. The process begins with detecting stations such as video cameras, satellites, and drones, which continuously monitor forest and remote areas.

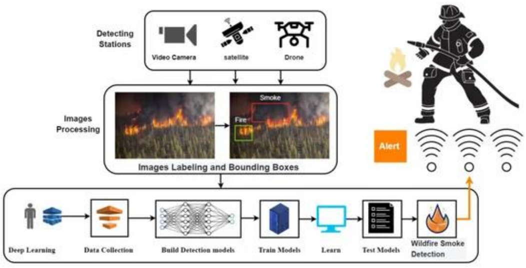


Fig. 1: Wildfire smoke-detection operation flowchart using deep learning

These sources capture real-time images and video streams of landscapes. The acquired visual data is then passed to the image processing stage, where images are analysed, labelled, and annotated with bounding boxes to clearly identify regions containing smoke and fire. This step helps in distinguishing wildfire-related patterns from background elements like clouds or fog.

2. LITERATURE SURVEY

[1] Gonçalves, L. A. O., et al. stated that their research focused on evaluating YOLO-based deep learning models for wildfire and smoke detection using both ground-based and aerial imagery. They analysed multiple YOLO variants under different environmental conditions such as illumination variation, background clutter, and smoke density. They used mixed ground and aerial wildfire image datasets. Their results showed that YOLO models achieved high detection accuracy with real-time inference capability. They concluded that YOLO-based approaches are well suited for early wildfire monitoring applications.

[2] Elhanashi, A., et al. In this they stated that their research focused on providing a comprehensive review of deep learning-based early fire and smoke detection systems. They analysed CNN, YOLO, and transformer-based models along with commonly used datasets and real-world deployment challenges. They reviewed multiple public and private wildfire datasets. Their analysis revealed that deep learning significantly improves detection accuracy compared to traditional methods. They concluded that further research is needed to improve robustness under fog, clouds, and early thin smoke conditions.

[3] Zhu, W., et al. In this they stated that their research focused on multiscale wildfire and smoke detection in complex forest environments using drone imagery. They proposed an improved YOLOv8 model with multiscale feature fusion to enhance small and distant smoke detection. They used UAV-based forest datasets captured under varying altitudes and backgrounds. Their model achieved higher precision and recall compared to baseline YOLOv8. They concluded that multiscale optimization improves wildfire smoke detection in UAV scenarios.

[4] Kaiming He, L., et al. In this they stated that their research focused on deep learning-based object detection techniques for forest fire smoke recognition. They evaluated different CNN and YOLO architectures for smoke detection. They used large-scale forest fire image datasets with varying smoke intensities. Their results demonstrated superior performance of deep learning models over traditional image-processing approaches. They concluded that object detection networks are effective for early smoke recognition.

[5] Ishtiaq, M., Won, et al. In this they stated that their research focused on improving fire and smoke detection using a modified YOLO architecture named YOLO-SIFD. They integrated sliced inference and fractal

dimension analysis to enhance small smoke region detection. They tested their model on wildfire image datasets. Their proposed approach achieved higher accuracy and reduced missed detections. They concluded that sliced inference significantly improves detection of thin and distant smoke.

[6] Hoang, V.-H., et al. In this they stated that their research focused on optimizing YOLO-based fire detection models using Bayesian hyperparameter tuning. They applied automated tuning to select optimal network parameters. They used fire and smoke image datasets for evaluation. Their tuned models achieved improved detection accuracy and faster convergence. They concluded that Bayesian optimization reduces manual effort while enhancing model performance.

[7] Panindre, P., et al. The study demonstrates that their research focused on developing an AI-IoT based wildfire detection system using vision models. They integrated deep learning-based image analysis with IoT sensor networks for real-time monitoring. They tested the system using simulated and real wildfire scenarios. Their results demonstrated reliable early detection and automated alert generation. They concluded that AI-IoT integration enhances real-time wildfire surveillance.

[8] Mukhiddinov, M., et al. In this they stated that their research focused on developing an optimized YOLOv8-based wildfire smoke detection system using UAV imagery, aiming to improve early-stage smoke identification. They introduced architectural enhancements including K-means++ anchor clustering, SPPF+ for improved spatial pyramid pooling, and Bi-FPN for stronger multiscale feature fusion. They used a UAV-based forestry smoke dataset containing diverse lighting and altitude conditions. Their optimized model achieved improved detection of thin and distant smoke plumes, outperforming standard YOLO models in both precision and inference speed. They concluded that such optimizations enable real-time deployment on lightweight UAV processors, significantly supporting early wildfire mitigation.

[9] Schroeder, W., et al. The study demonstrates that their research focused on thermal-based early wildfire smoke detection using satellite observations. They analysed MODIS and VIIRS thermal datasets under different atmospheric conditions. They used large-scale satellite data for evaluation. Their study showed limitations in detecting early thin smoke due to low thermal contrast. They concluded that thermal-based methods alone are insufficient for early wildfire detection.

[10] Reddy, K., et al. In this they stated that their research focused on ground-based optical and infrared surveillance systems for early forest fire smoke detection. They combined visible and infrared imaging techniques to improve detection reliability. They used ground surveillance data collected from forest regions. Their system improved detection accuracy compared to single-spectrum methods. They concluded that multi-sensor approaches enhance early smoke detection but are sensitive to weather conditions.

[11] Chen, T., et al. In this they stated that their research focused on image-processing techniques for outdoor smoke detection in natural environments. They analyzed color, motion, and texture-based features to identify smoke regions. They used outdoor surveillance image datasets captured under varying illumination and background conditions. Their results showed reasonable detection performance in controlled scenes. They concluded that traditional image-processing techniques lack robustness compared to deep learning methods.

[12] Dimitropoulos, K., et al. The study demonstrates that their research focused on motion analysis techniques for early outdoor smoke detection. They extracted temporal motion features to differentiate smoke from background movement. They used outdoor video datasets for evaluation. Their approach achieved acceptable detection in static scenes.

They concluded that motion-based methods are sensitive to camera motion and environmental disturbances.

[13] Merino, L., et al. In this they stated that their research focused on UAV-based remote sensing systems for forest fire monitoring. They utilized UAV platforms to capture high-resolution aerial imagery for fire detection. They tested their system on forest monitoring scenarios. Their results demonstrated improved situational awareness and coverage. They concluded that UAVs are effective for wildfire monitoring but face endurance and data processing challenges.

[14] Alexis, K., et al. In this they stated that their research focused on multi-UAV cooperative systems for large-area wildfire monitoring. They proposed coordinated UAV control and data sharing strategies. They evaluated their system in simulated wildfire environments. Their approach improved coverage and detection efficiency. They concluded that cooperative UAV systems significantly enhance large-scale wildfire surveillance.

[15] Muhammad, K., et al. In this they stated that their research focused on CNN-based smoke detection for resource-constrained UAV applications. They designed lightweight CNN architectures to reduce computational complexity. They used UAV-captured smoke image datasets. Their model achieved a balance between accuracy and real-time performance. They concluded that lightweight CNNs are suitable for onboard UAV smoke detection.

3. Proposed System

The proposed methodology for real-time wildfire smoke detection follows a structured sequence of operations, starting from image acquisition to alert generation. The system is designed to ensure accurate early-stage smoke detection with minimal latency and high reliability as shown in Fig. 2.

Image Acquisition: The first step in the proposed system is image acquisition. Forest and wildfire-prone areas are continuously monitored using Unmanned Aerial Vehicles (UAVs), surveillance cameras, or aerial monitoring platforms. These devices capture high-resolution images under various environmental conditions such as daylight, low light, fog, haze, and different smoke densities including thin, medium, and dense smoke. The captured images are then transmitted to the processing unit for further analysis. This step ensures continuous and large-scale monitoring of vulnerable forest regions.

Image Preprocessing: The third step involves preprocessing the images to enhance quality and maintain uniformity before training or inference. All images are resized to 640 × 640 pixels, which is the standard input size for YOLOv8. Pixel values are normalized between 0 and 1 to ensure stable gradient updates and faster convergence during training. Noise reduction techniques such as Gaussian filtering are applied to minimize atmospheric disturbances and unwanted image artifacts. Additionally, data augmentation techniques are used to improve generalization performance. These techniques help the model handle variations in lighting, background complexity, and environmental conditions.

Model Selection – YOLOv8: The fourth step involves selecting YOLOv8 as the object detection model. YOLOv8 is a single-stage deep learning model optimized for high speed and accuracy. It processes the entire image in a single forward pass, enabling real-time detection. The model consists of a backbone for extracting hierarchical spatial features, a neck for multi-scale feature fusion, and a head for predicting bounding boxes, objectness scores, and smoke classification. This architecture makes YOLOv8 highly effective for detecting small and distant smoke regions.

Model Training: In the fifth step, the annotated dataset is used to train the YOLOv8 model. The training process is configured with an input image size of 640 × 640 pixels, an adaptive learning rate, and an optimizer such as

Stochastic Gradient Descent or Adam. The batch size is selected based on available GPU memory, and the training process runs for multiple epochs until convergence is achieved. The loss function combines bounding box regression loss, objectness loss, and classification loss. During training, the model iteratively updates its weights to minimize the total loss and improve detection accuracy.

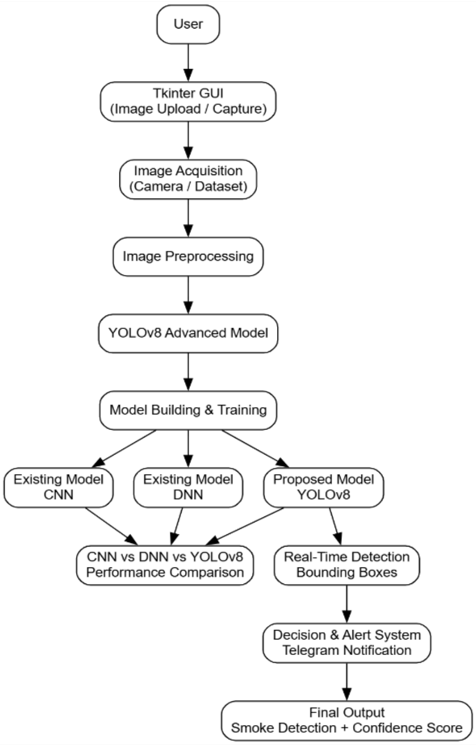


Fig. 2**:** Block diagram of the proposed system architecture.

Model Validation and Testing: After training, the model is evaluated using a separate validation and testing dataset. This step measures the performance of the model using evaluation metrics such as precision, recall, mean Average Precision (mAP), and Frames Per Second (FPS). Precision indicates the correctness of detections, recall measures the ability to detect actual smoke instances, mAP provides overall detection performance, and FPS determines the real-time processing capability. This evaluation ensures that the model meets both accuracy and speed requirements.

Alert Generation: When smoke is detected, the alert generation module is activated. The detected image is saved along with its confidence score and timestamp. A real-time alert is generated and transmitted through a Telegram bot. The alert message includes the detection image, confidence level, and time of detection. This ensures immediate notification to authorities or monitoring personnel for quick response and disaster management.

GUI Display (Tkinter Integration): The final step involves displaying the detection results through a Tkinter-based graphical user interface. The GUI allows users to upload or capture images and view detection results visually. It displays bounding boxes around smoke regions, shows confidence scores, and indicates system status such as "Smoke Detected" or "No Smoke." This interface improves usability, monitoring convenience, and system interaction.

Proposed YOLOv8 Detection Model

The proposed system utilizes the YOLOv8 (You Only Look Once – Version 8) model as the primary object detection framework for real-time wildfire smoke detection. YOLOv8 is a single-stage deep learning detector designed to perform object localization and classification simultaneously in a single forward pass. In this application, the input to the YOLOv8 model consists of pre-processed forest images, while the output is the detected smoke region along with bounding box coordinates and confidence scores as shown in Fig. 3. The model is optimized for high detection accuracy and real-time performance, making it suitable for UAV-based wildfire monitoring systems.

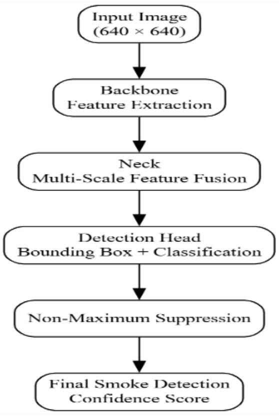


Fig. 3: Proposed YOLOv8 detection model

Step 1: Image Input: In the first step, pre-processed images resized to 640 × 640 pixels are provided to the YOLOv8 model. These images represent forest scenes that may contain smoke under different environmental conditions such as haze, cloud interference, illumination variations, and complex backgrounds. The standardized input size ensures compatibility with the network architecture and enables efficient feature extraction.

Step 2: Backbone Feature Extraction: In the second step, the backbone network of YOLOv8 extracts hierarchical spatial features from the input image. The convolutional layers initially learn low-level features such as edges, gradients, and simple patterns. As the network depth increases, deeper layers capture more complex features including smoke textures, plume shapes, and structural variations. This hierarchical feature learning enables the model to represent subtle smoke characteristics effectively, even in challenging forest environments.

Step 3: Neck – Multi-Scale Feature Fusion: In the third step, the neck component performs multi-scale feature fusion using feature pyramid techniques. This process combines feature maps from different resolution levels to enhance detection capability across varying object sizes. By integrating both high-resolution and low-resolution feature information, the system improves its ability to detect small and thin smoke, medium smoke regions, and large dense smoke plumes. Multi-scale fusion plays a critical role in handling complex forest backgrounds and distant smoke patterns.

Step 4: Detection Head Prediction: In the fourth step, the detection head generates predictions for potential smoke regions. For each candidate region, the model predicts bounding box coordinates including the center position and dimensions, an objectness score indicating the probability of smoke presence, and the class probability corresponding to the smoke category. These predictions are produced simultaneously in a single-stage detection process, which significantly reduces computational latency compared to two-stage detectors.

Step 5: Non-Maximum Suppression (NMS): In the fifth step, Non-Maximum Suppression is applied to eliminate redundant overlapping bounding boxes. Since multiple predictions may correspond to the same smoke region, NMS retains only the bounding box with the highest confidence score while discarding lower-confidence overlapping detections. This step ensures precise localization and prevents duplicate predictions.

Step 6: Output Generation: In the sixth step, the final detection output is generated. The output consists of the detected smoke region, bounding box visualization drawn over the image, and the associated confidence score. This detection result is then forwarded to the alert generation module and the graphical user interface for further processing and display.

4. Results Analysis

The performance of the proposed YOLOv8-powered wildfire smoke detection system was evaluated using the prepared smoke detection dataset under diverse environmental conditions. The dataset includes images captured from surveillance cameras and forest monitoring systems, representing various real-world challenges such as illumination variations, background complexity, haze, and different smoke densities. The objective of the result analysis is to assess detection accuracy, localization capability, real-time performance, and alert generation efficiency of the proposed system.

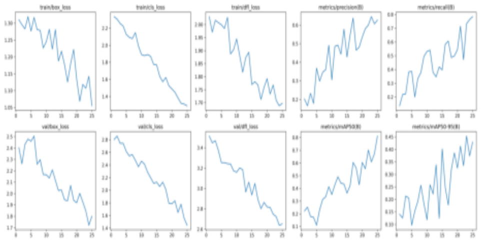


Fig. 4: Performance curves of the existing DNN model.

Fig. 4 shows the performance curves of the existing DNN model, illustrating the training loss, validation loss, precision, recall, and MAP metrics across different epochs. The training loss curve demonstrates a gradual decreasing trend, indicating that the model effectively learns feature representations from the smoke detection dataset. Similarly, the validation loss also reduces consistently with minor fluctuations, suggesting that the model maintains reasonable generalization without severe overfitting. Fig. 5 shows the performance curves of the existing CNN model, illustrating the variation of training loss, validation loss, precision, recall, and mAP metrics over multiple epochs. The training loss curve shows a consistent downward trend, indicating that the CNN model effectively learns hierarchical spatial features from the smoke detection dataset. Although small fluctuations are observed during intermediate epochs, the overall reduction in loss confirms stable optimization and proper convergence of the model. The validation loss also decreases steadily along with the training loss, suggesting that the CNN model maintains good generalization capability without significant overfitting. The gap between training and validation loss remains minimal, which indicates that the learned convolutional features are effectively transferred to unseen test samples.

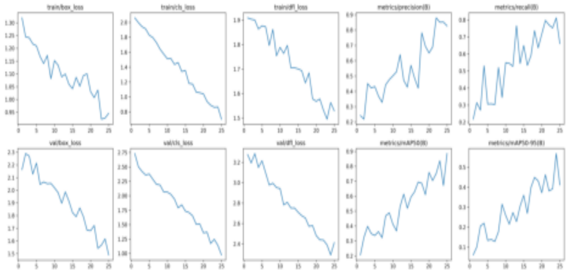


Fig. 5: Performance curves of the existing CNN model.

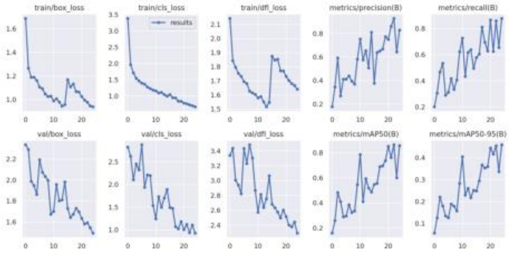
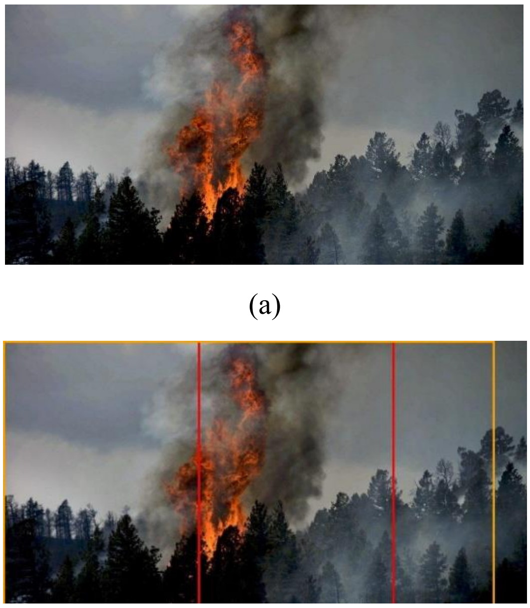


Fig. 6: Performance curves of the proposed YOLOv8 model.

The mAP0.5 metric shows consistent growth throughout the training process, confirming improved classification and localization performance. Additionally, the mAP@0.5:0.95 curve indicates progressive enhancement in bounding box accuracy under stricter IoU thresholds. Compared to the DNN model, the CNN demonstrates better spatial feature extraction and improved detection stability due to its convolutional structure. However, particularly in scenarios involving thin or dispersed smoke patterns. Overall, its performance is still limited in terms of real-time detection efficiency and advanced bounding box regression when compared with the proposed YOLOv8-based system. Fig. 6 shows the performance curves of the proposed YOLOv8 model, illustrating the variation of training box loss, classification loss, distribution focal loss (DFL), validation losses, precision, recall, and map metrics across training epochs. The training loss curves, including box loss, classification loss, and DFL loss, exhibit a consistent decreasing trend as the epochs progress. This indicates that the model effectively optimizes both localization and classification parameters. Although minor fluctuations are observed in intermediate epochs, the overall convergence behaviour remains stable, demonstrating efficient feature learning and gradient optimization. The mAP0.5 metric shows strong upward progression, confirming high detection accuracy at standard IoU thresholds. Furthermore, the mAP@0.5:0.95 curve also increases steadily, demonstrating improved localization precision even under stricter overlap criteria. These results indicate that the

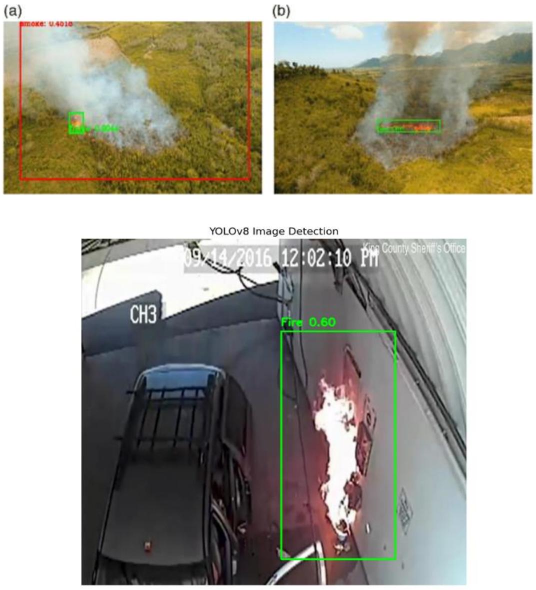
YOLOv8 model not only classifies smoke accurately but also provides precise bounding box localization.


(a)

(b)

Fig. 7: Prediction results of wildfire smoke detection. (a) Input Image, (b) output Image.

Fig. 7 illustrates the performance of the YOLOv8-based wildfire smoke detection system through a comparative visualization of the input and output images.



(c)

Fig. 8: Prediction results of wildfire fire detection.

- **(a) Input Image:** The input image represents a raw scene captured from a surveillance or ground-based camera. It contains natural environmental elements such as trees, vegetation, sky, and background terrain where smoke is present. The smoke appears as diffused, semi-transparent regions blending with the surroundings, which makes manual identification challenging due to variations in lighting conditions, background clutter, and texture similarity.
- **(b) Output Image:** The output image shows the detection results generated by the trained YOLOv8 model. The system accurately identifies smoke regions and highlights them using bounding boxes. Each detected region is labeled as “smoke” along with a confidence score that reflects the model’s prediction strength. The bounding boxes are tightly aligned with the smoke areas, demonstrating precise localization. The model effectively distinguishes smoke from visually similar elements such as clouds, fog, or dust, resulting in reduced false positives. This confirms the robustness of the trained model in detecting smoke under diverse environmental conditions and supports real-time monitoring capabilities.

Fig. 8 presents the detection of visible fire regions using the trained YOLOv8 model within the system framework. The image clearly highlights active fire areas with bright, high-intensity colors such as orange, red, and yellow flames. The model accurately detects these regions and encloses them within bounding boxes along with high confidence scores, demonstrating precise localization. It effectively captures flame characteristics including shape, intensity, and contrast against the background, even in scenes with vegetation, shadows, and varying illumination. The results confirm consistent detection performance for both smoke and fire, reinforcing the system's effectiveness as a comprehensive wildfire monitoring solution.

5. Conclusion

The proposed wildfire smoke detection system using YOLOv8 has been successfully designed and implemented to detect smoke from wildfire images with high accuracy and real-time performance. In this project, deep learning–based object detection is applied using the advanced capabilities of YOLOv8 to identify smoke regions in images efficiently. The system integrates multiple components including image acquisition, preprocessing, model training, and detection output visualization through a user-friendly Tkinter graphical interface. The trained model effectively distinguishes smoke from background elements such as clouds, fog, and dust by learning robust visual features from the dataset. The use of deep neural networks improves detection precision compared to traditional machine learning techniques. Experimental results demonstrate that the proposed system achieves improved detection accuracy, reduced false positives, and faster inference time. The GUI integration allows users to upload images easily and visualize detection results with bounding boxes and confidence scores.

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