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Edge-AI Enabled Real-Time Forest Fire Detection and Early Warning Framework Using YOLOv8 and IOT Technologies

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Abstract
Forest fires are among the most destructive natural disasters, causing significant environmental damage, biodiversity loss, economic disruption, and threats to human life. Conventional fire monitoring techniques, such as watchtowers, satellite imaging, and manual patrols, often suffer from delayed detection, limited coverage, and high operational costs. This paper proposes an Edge-AI Enabled Real-Time Forest Fire Detection and Early Warning Framework using the YOLOv8 object detection model and Internet of Things (IoT) technologies. The proposed framework performs real-time fire and smoke detection directly on edge devices, reducing detection latency, bandwidth consumption, and dependence on cloud connectivity, making it suitable for remote forest environments. Environmental data collected from IoT sensors, including temperature, humidity, smoke concentration, carbon monoxide (CO), and air quality, are integrated through a sensor fusion mechanism to validate visual detections and minimize false alarms. The framework comprises five layers: Data Acquisition, Edge AI Processing, IoT Sensing, Cloud Communication, and Emergency Alert Generation. Detection results, GPS location, confidence score, timestamp, and sensor readings are transmitted to a cloud dashboard, where automated alerts are delivered to forest authorities via SMS, email, mobile applications, or web platforms. The proposed framework provides low-latency processing, improved detection accuracy, reliable early warning, and scalable deployment for intelligent wildfire monitoring. Future work includes integrating thermal imaging, Vision Transformers, Explainable AI, federated learning, autonomous drones, and Digital Twin technology to further enhance wildfire prediction and disaster management.

Keywords: Forest Fire Detection, Edge AI, YOLOv8, Internet of Things (IoT), Sensor Fusion, Early Warning System.

1. Introduction

Forest fires are among the most destructive natural disasters, causing severe environmental damage, biodiversity loss, economic losses, and threats to human life. Increasing temperatures, prolonged droughts, and human activities have significantly increased the frequency and intensity of wildfires, making early and reliable fire detection essential. Conventional detection methods, such as watchtowers, satellite monitoring, and manual patrols, often suffer from limited coverage, delayed detection, high operational costs, and dependence on human intervention. Recent advancements in Artificial Intelligence (AI), Deep

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Learning (DL), Edge Computing, and the Internet of Things (IoT) have enabled intelligent real-time wildfire monitoring. In particular, the YOLOv8 object detection model provides high accuracy and fast inference for detecting fire and smoke in images captured by cameras and UAVs. However, many existing systems rely on cloud-based processing, resulting in communication latency, high bandwidth usage, and poor performance in remote forest regions with limited connectivity. To overcome these limitations, this paper proposes an **Edge-AI Enabled Real-Time Forest Fire Detection and Early Warning Framework Using YOLOv8 and IoT Technologies**. The framework combines optimized YOLOv8-based edge inference with IoT sensor fusion (temperature, humidity, smoke, CO, air quality, and wind speed), GPS localization, cloud monitoring, and automated emergency alerts. The proposed architecture consists of five layers: **Data Acquisition, Edge AI Processing, IoT Sensing, Cloud Communication, and Emergency Alert Generation**. By integrating visual detection with environmental sensing, the system achieves low-latency, high-accuracy wildfire detection, reduces false alarms, minimizes bandwidth consumption, and enables rapid emergency response. The framework is scalable, cost-effective, and suitable for deployment in remote forest environments, providing an efficient solution for intelligent wildfire monitoring and early warning.

2. Related Work

Forest fire detection has gained significant attention due to the increasing frequency of wildfires and their environmental and economic impacts. Early advancements by Redmon et al. [1] introduced the YOLO framework, enabling fast and accurate real-time object detection. Building on this, Jiao et al. [2] and Wang et al. [3] applied YOLO-based models for UAV-assisted fire and smoke detection, demonstrating improved monitoring capabilities. Later studies integrated edge computing with UAVs to reduce latency and enhance real-time processing [4]. Recent YOLOv8-based approaches further improved fire detection accuracy, localization, and inference speed through enhanced feature extraction and optimized architectures [5–7]. Researchers have also explored the integration of UAVs, IoT, and Edge AI for wildfire monitoring. Bushnaq et al. [8] highlighted the potential of UAV-IoT networks for large-scale environmental surveillance, while Almeida et al. [9] proposed a lightweight edge-based CNN model for real-time fire and smoke detection. A recent review [10] emphasized that combining AI, IoT, cloud computing, and edge computing can significantly improve wildfire prevention and detection. Despite these advancements, existing methods often rely solely on image-based detection, depend heavily on cloud computing, or lack multimodal sensor fusion, leading to higher latency and false alarms. Few studies integrate YOLOv8, Edge AI, IoT environmental sensors, GPS localization, and automated emergency alerts into a unified framework. To address these limitations, the proposed **Edge-AI Enabled Real-Time Forest Fire Detection and Early Warning Framework Using YOLOv8 and IoT Technologies** combines optimized YOLOv8-based vision, Edge AI, IoT sensor fusion, GPS-based localization, cloud monitoring, and automated alert generation to achieve accurate, low-latency, and scalable wildfire detection with reduced false alarms.

Table 1. Comparison Table

Ref.	Method	Technology Used	Advantages	Limitations
Paper 1	CNN-Based Fire Detection	CNN, Cctv	Good Classification Accuracy	Cannot Localize Fire, Slower Inference
Paper 2	Yolov5 Fire Detection	Yolov5, Computer Vision	Real-Time Detection	Cloud Dependency, False Alarms
Paper 3	Iot Forest Monitoring	Iot Sensors, Lorawan	Continuous Environmental Monitoring	No Image-Based Verification
Paper 4	Uav Fire Detection	Drone, Thermal Camera, Ai	Covers Inaccessible Forest Areas	Limited Battery Life And Flight Time
Paper 5	Edge Ai Fire Detection	Edge Computing, CNN	Low Latency, Reduced Bandwidth	Limited Sensor Integration
Paper 6	Yolov7 + Iot	Yolov7, Iot	Improved Accuracy	No Multimodal Sensor Fusion
Proposed Work	**Edge-Ai Enabled Real-Time Forest Fire Detection And Early Warning Framework**	**Yolov8, Edge Ai, Iot Sensors, Gps, Cloud, Automated Alerts**	**Real-Time Detection, Low Latency, Sensor Fusion, Gps Localization, Automated Alerts, Scalable Architecture**	**Designed To Overcome The Limitations Of Existing Methods**

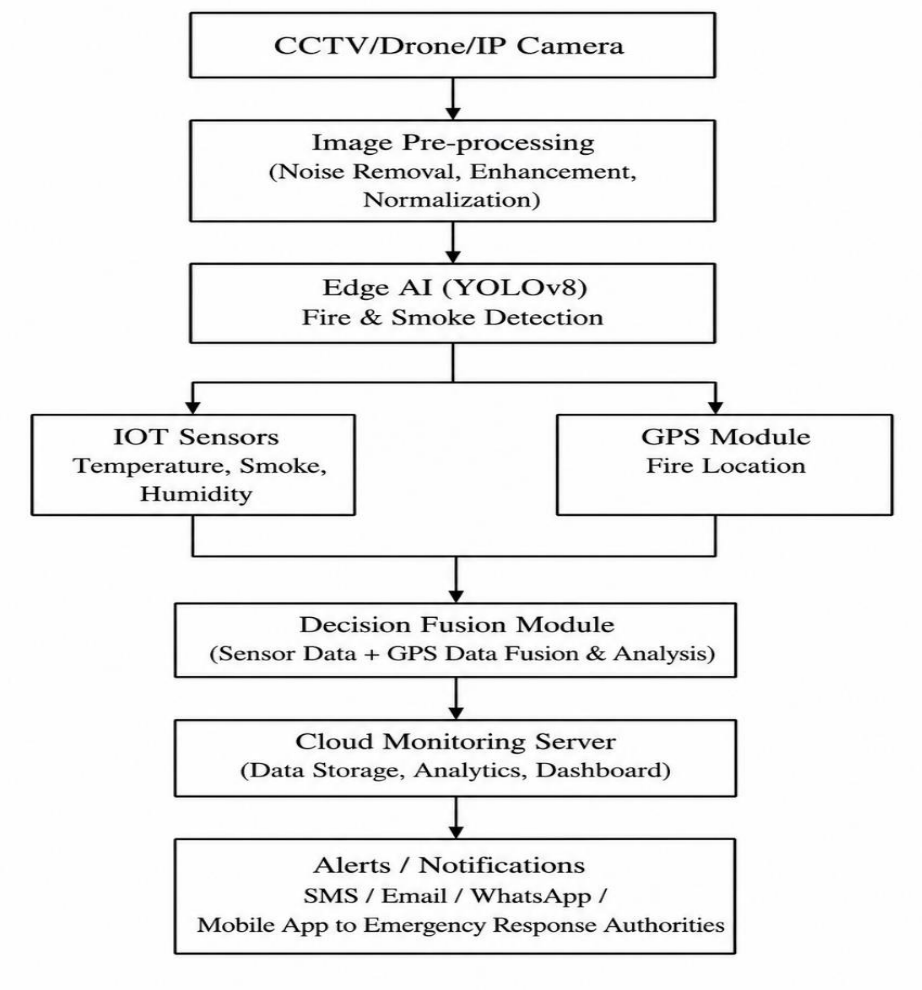
3. Methodology

The proposed Edge-AI Enabled Real-Time Forest Fire Detection and Early Warning Framework Using YOLOv8 and IoT Technologies contains a systematic methodology for forest fire detection using computer vision with the assistance of Edge AI (Artificial Intelligence) and IoT (Internet of Things). The methodology comprises seven (7) stages which are; Data Collection, Data Preprocessing, YOLOv8 Model

Training, Edge AI Deployment, IoT Sensors Integration, Decision Fusion, and Automated Early Warning Generation.

3.1 System Architecture

Figure 1. YOLOv8-Based Forest Fire Detection System Architecture



3.2 Data Collection

The first step in the methodology involves the collection of forest fire and smoke images from public datasets, surveillance cameras, UAVs (Unmanned Aerial Vehicles), and CCTV (Closed-Circuit Television) cameras. The data consists of all-day, night, fog, smoke, cloudy, and bright images of forest fires. The data collected comprised images captured during the day, night, fog, and smoke, cloudy, and bright conditions. Apart from the images, temperature, humidity, smoke, CO, and air quality sensors were used to collect environmental data around the forest.

3.3 Data Preprocessing

The second stage in the methodology involved preprocessing the images before they are fed into the deep learning model. The preprocessing step entailed rescaling all the images to 640 × 640 pixels, image normalization, removing noisy samples, and redundant images. The data was augmented using techniques like rotation, horizontal flipping, scaling, enhancement, contrast adjustment, and mosaic for better performance and increased data diversity. All fire and smoke images were annotated using the YOLO annotation software.

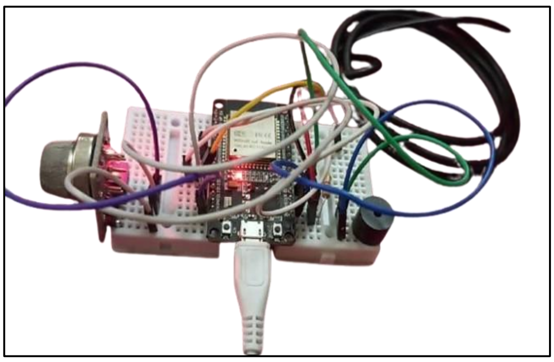
3.4 YOLOv8 Model Training

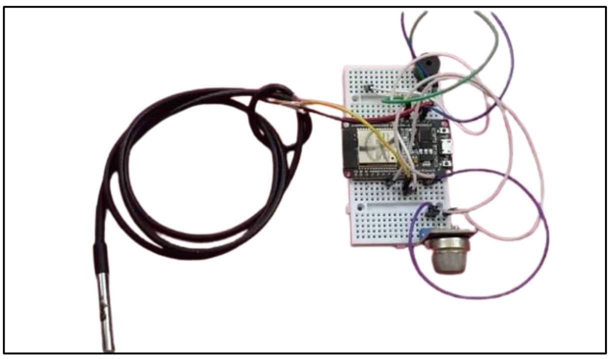
The preprocessed dataset is utilized for training the YOLOv8 object detection model. The data is split into training, validation, and test sets. During the training process, the model learns the underlying visual patterns that differentiate fire and smoke in images captured under different conditions. The model's hyper parameters, including learning rate, batch size, image resolution, number of epochs, and confidence threshold, are fine-tuned to enhance the detection accuracy of fire and smoke while avoiding overfitting. The performance of the trained model is evaluated using standard metrics such as Precision, Recall, F1-Score, mAP (mean Average Precision), and IoU (Intersection over Union). The best performing model with the highest validation accuracy is selected for deployment.

Figure 2: Components and Circuit Diagram

Temperature sensor

MQ135 Gas Sensor





3.5 Edge AI Deployment

The trained model is deployed on an Edge AI device, such as a NVIDIA Jetson Nano, Raspberry Pi AI computer, or other embedded systems, for real-time fire and smoke detection. The video feed from the surveillance cameras is first preprocessed on the Edge AI device. Then, the YOLOv8 model is applied to detect fire and smoke, generate bounding boxes, and predict the confidence score of the detected objects in the video frames. The Edge AI deployment ensures faster inference with reduced bandwidth usage since the video does not need to be transmitted to the cloud. This approach also enables continuous processing of video feeds in remote locations without internet access.

3.6 IoT Sensor Deployment

The IoT sensors are deployed to monitor the surrounding environment and collect data such as temperature, humidity, smoke, CO, CO2, wind speed, and air quality. The information is transmitted to the edge AI device over a wireless network using protocols such as LoRaWAN, Wi-Fi, ZigBee, NB-IoT, or 4G/5G.

3.7 Decision Fusion and Fire Verification

The outputs of the YOLOv8 Detection module and IoT sensors are fused using a multimodal decision fusion algorithm. The visual detections are verified using the sensor data. Only detections with confidence level above a certain threshold are reported as fire events by the fusion module. False alarms triggered by sunlight reflection, fog, dust, clouds, or nearby objects are thus reduced, while detection accuracy is improved.

Fire Detection Decision

$$D = \begin{cases} 1, & \text{if } C_{YOLO} \geq T_c \wedge S_{fusion} \geq T_s \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where:

- D= Fire decision (1 = Fire detected, 0 = No fire)
- CYOLO = Confidence score produced by YOLOv8
- Tc = Confidence threshold
- Sfusion = Sensor fusion score
- Ts = Sensor threshold

Sensor Fusion Score:

$$S_{fusion} = \sum_{i=1}^{n} w_i x_i \quad (2)$$

Where

- xi = normalized sensor value
- wi = weight assigned to each sensor
- n = number of IoT sensors

The weights satisfy:

$$\sum_{i=1}^{n} w_i = 1 \qquad (3)$$

Detection Confidence

YOLOv8 predicts the fire confidence as

CYOLO = P(Fire | F)

where

- F = input image frame
- P(Fire|F) = probability that the frame contains fire.

3.8 Cloud Monitoring and Early Warning

After detecting any fire event, the system uploads an alert that contains the fire image, GPS location, timestamp, confidence level, and sensor data to a cloud monitoring server. The cloud dashboard displays the uploaded information for review. The Early Warning Module generates emergency alerts that contain the fire image, GPS location, confidence level, and sensor data. The alerts are sent to forest rangers, fire brigade, and disaster management authorities via SMS, email, mobile apps, WhatsApp, or alarm systems. The early warning about fire helps authorities take immediate action to minimize the damage caused.

4. Results and Discussions

Figure 2. Training Loss Curve

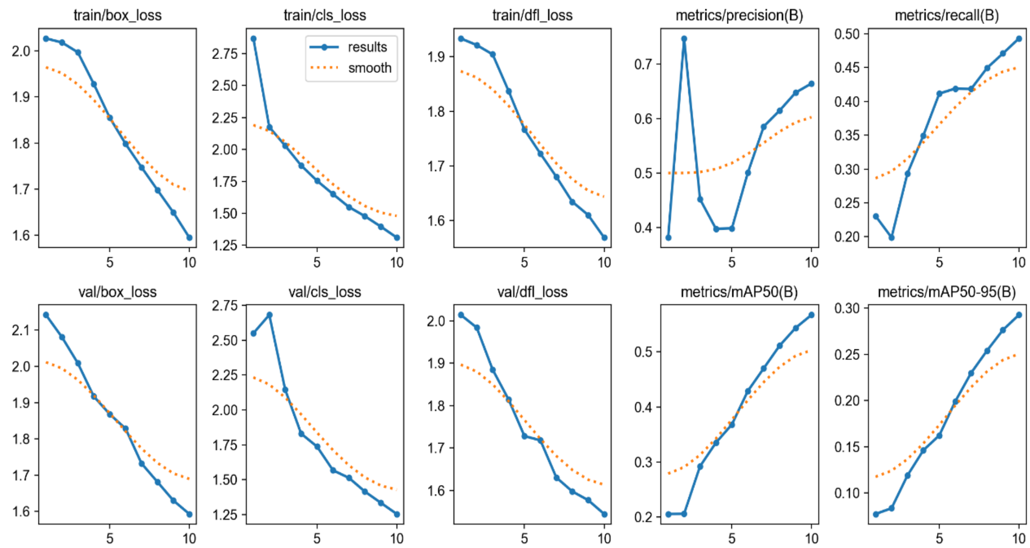


Figure 3. Confusion Matrix and Normalized Confusion Matrix

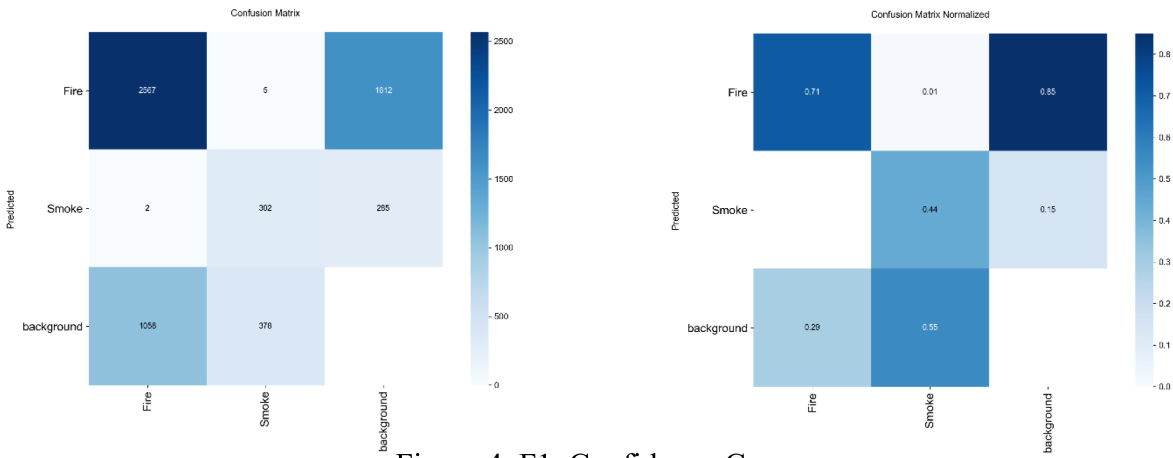
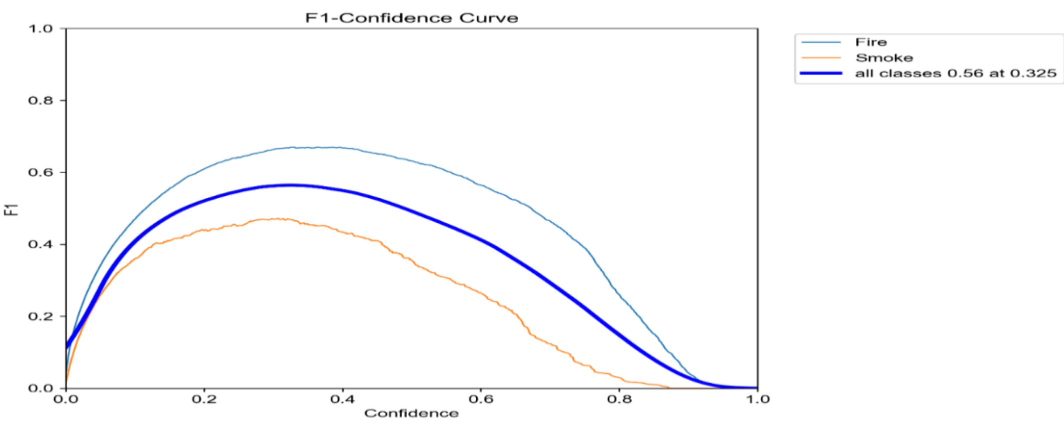


Figure 4. F1–Confidence Curve



4. Conclusion

This paper presents an Edge-AI enabled real-time forest fire detection and early warning framework that integrates YOLOv8, Edge AI, IoT sensors, cloud computing, GPS tracking, and an automated alert system for intelligent wildfire monitoring. Unlike conventional cloud-based approaches, the proposed framework performs on-device fire detection using YOLOv8, enabling low-latency inference with reduced bandwidth consumption. Sensor fusion using temperature, humidity, smoke, CO, and air quality sensors enhances detection reliability and significantly reduces false alarms caused by environmental factors such as sunlight, fog, haze, and dust. The system provides real-time location tracking and multi-channel alerts through SMS, email, WhatsApp, and mobile applications. Designed for remote environments with limited internet connectivity, the framework offers a scalable, cost-effective, and energy-efficient solution for forest conservation, wildlife protection, climate change adaptation, and disaster risk reduction through rapid, accurate, and intelligent wildfire detection.

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