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Development of a Multimodal Artificial Intelligence Framework for Forest Fire Prediction

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Abstract
This study presents a Multimodal Artificial Intelligence Framework (MAIF) that integrates real-time sensor data and visual imagery to enhance forest fire detection accuracy, responsiveness, and reliability in remote environments. The system combines ensemble classification models such as Random Forest, SVM, KNN, XGBoost and Gradient Boosting with YOLOv8-based image recognition to detect fire risk patterns and visual indicators such as smoke and flame contours. A custom-built Forest Fire Capturing Device (FFCD), equipped with an ESP32 microcontroller and LoRaWiFi, was deployed in Omo forest, Nigeria, to collect heterogeneous environmental data. Visual inputs from ground cameras and drones were fused with sensor-based predictions to minimize false positives and improve generalization. The base classifiers showed performances of 0.98, 0.96, 0.93, 0.98, 0.98 for RF, SVM, KNN, XGBoost and GB, respectively with heterogeneous sensor datasets of 10,334 rows and 13 columns while meta-classifier and YOLOv8 module both achieved 0.98 accuracy, with significantly lower false positive rates compared to single-modality systems. Upon confirmed detection, the system automatically dispatched timestamped fire images via email, enabling rapid situational awareness and emergency response coordination.

Keywords: *Multimodal Framework, Heterogeneous sensor data, Low resource environment, Forest fire*

1 Introduction

While wildfires play a role in ecological balance, their intensification due to anthropogenic factors has disrupted this equilibrium. In African tropical forests, their rising frequency contributes to green house gas emissions, land degradation and biodiversity loss [1]. Unlike other hazards, wildfires require specific conditions: fuel availability, ignition and spread dynamics. They are classified into six generations, each with distinct features and impacts. Wildfire generations evolve from basic fuel and spread dynamics to complex, uncont- rollable phenomena. Fourth-generation fires threaten both nature and urban areas, while fifth-generation events overwhelm national response systems. Sixthgeneration wildfires create their own weather, resisting even aerial suppression [2]. Their ignition often stems from human activity, influenced by environmental and land cover conditions.

Sensor-based fire prediction is increasingly used in the Internet of Things (IoT) for proactive fire mitigation. IoT connects physical devices embedded with sensors and software to share data over the internet [3]. IoT-enabled sensors function independently, facilitating uninterrupted environmental monitoring. Forest fire detection systems use five types of sensors which are smoke, light, gas, temperature and composite to identify early fire indicators [4]. Temperature and smoke sensors are most common due to their durability in harsh environments and real-time data capture. These sensors communicate via Wireless Sensor Networks (WSNs) to cloud servers for analysis. Alerts are instantly sent to authorities and local communities, with severity-based notifications for nearby residents.

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Forest fires have caused severe damages to wildlife, humans, and forest resources. Traditional firefighting methods relying on ground crews are limited and risky. Machine learning models often misclassify fires due to ambiguous flame and temperature readings. Inconsistent material labeling further hampers accurate fire categorization. Deep learning techniques offer speed but suffer from low accuracy and overfitting. This study uses a Stack Ensemble meta-classifier with feature selection to improve prediction accuracy, tailored to regional fire behavior. Intelligent Forest Fire Automation Systems help conserve wildlife, prevent forest degradation, and reduce economic losses by enabling early fire prediction and response. Prior systems were often costly, complex, and ineffective in remote areas lacking internet connectivity. They also suffered from limited predictive intelligence, prompting the need for more advanced and accessible solutions.

2 Related works

Wireless Sensor Networks (WSNs) use distributed sensors to monitor environmental factors like temperature, sound, and humidity. Due to limited memory and processing power, sensor nodes rely on a central base station for data aggregation and communication with users. Nodes are typically battery-powered with low computing capacity [5], they balance energy use to remain autonomous over time. Beyond data collection, they also perform in-network analysis and aggregation to support efficient system operations.

Sensor nodes in Wireless Sensor Networks (WSNs) vary in capability and are often built with spherical designs to endure harsh tropical conditions [6]. Basic nodes monitor single phenomena, while advanced ones integrate acoustic, optical, and magnetic sensing. Communication abilities also differ, some nodes simply transmit data, while others handle processing and aggregation. High-capacity nodes enhance system intelligence through onboard computation and data fusion. Wireless sensors track heat, smoke, and gas levels, while cameras visually confirm fire through flame and smoke patterns. This multi-layered setup boosts detection accuracy and spatial localization, ideal for complex and dynamic forest environments [7].

Base stations serve as central hubs with greater resources for data collection and command transmission. Network topology influences data flow efficiency, with structures like star, mesh and cluster. Routing protocols guide data transmission, affecting energy use and reliability. Deployment strategies whether random, manual, or automated, impact coverage and network lifespan. Intelligent fire detection systems use techniques like CNNs, fuzzy logic and color models for high-accuracy detection across environments. IoT-based systems integrate secure communication, cloud and fog technologies and algorithms like Dijkstra’s for efficient fire prediction and alerting [8].

The Internet of Things (IoT) connects physical objects equipped with sensors, actuators, and communication tools to interact seamlessly with each other and the Internet. In smart forests, intelligent systems utilize IoT-generated data to enhance decision-making and operational efficiency. Data analytics plays a vital role in optimizing forest services through pattern recognition and predictive insights. Devices like embedded systems, temperature sensors, and Raspberry Pi are key tools for data collection and analysis in these environments [9]. IoT has many potential applications in various domains, such as wearables, smart homes, smart cities, smart health, smart agriculture, smart industry and smart environment.

Development of an AI-based forest fire prediction model using a stack ensemble meta-classifier involves the deployment of an ESP32-powered Forest Data Capturing Device (FDCD) for real-time sensor data collection and evaluating both the stack ensemble model and YOLOv8 for image-based fire detection. The system also includes automated email alerts with images to inform forest administrators of fire-related activities. The device was deployed to collect real-time sensor data, which was analysed using five machine learning models and a stack meta-classifier for enhanced fire prediction. The integration of YOLOv8 architecture helped reduce false positives, as illustrated in [10], the study enhanced YOLOv8 model and it achieved: Precision: 98.7%, Recall: 97.9%, False Positive Rate (FPR): Reduced to 0.43%, outperforming prior YOLOv5 benchmarks and also improving detection accuracy across diverse forest types and supporting more effective resource management and disaster prevention [11].

3 Methodology

3.1 Feature Engineering and Model Validation

Data was gathered through sensor and feature engineering was carried out to extract relevant information from the datasets. To assess model performance, we employed K-fold cross-validation on the prepared datasets which ensures that our model generalizes well to unseen data. Stack ensemble meta-classifier model was leveraged by combining multiple base models to improve prediction accuracy. The ensemble approach enhances the system's reliability and robustness.

3.2 Image Classification with YOLOv8

In the second phase of prediction, YOLOv8 (You Only Look Once) algorithm was utilized for efficient and accurate image classification on fire and non-fire images. YOLOv8 identifies fire-related patterns, aiding in early detection. The design and deployment of the Intelligent Forest Fire Prediction System (IFFPS) involved the integration and wiring of intelligent sensors with the connected microcontroller unit (ESP32). The system was successfully installed and subjected to functional testing to ensure proper operation. After connecting the microcontroller and components, coding was performed using Arduino Sketch. Programming language to achieve the required tasks. The design was rechecked to identify performance of the system functionalities, testing was conducted to validate the data collection and transmission's performance. The data capturing sensors which includes (Temperature, Humididty, Gas, Rain sensors, Camera and LoRaWiFi) are all mounted on ESP 32 which represents the system's micro-controlling unit or processing unit as seen in Figure 1. Three of this unit were mounted strategically within the forest environment to garner data and transmit it through LoraWiFi. The transmitted data was received through LoRaWiFi that is connected to the ESP 32. The MiFi with a router transmits the data over a long distance to a database at the remote base station. The data was divided into two groups, fire and non-fire images from the camera and other data from the sensors.

The rich library available for Python development allows simplified imple-mentation. For the development of mobile applications, several choices of platforms are available. LoRaWi-Fi technology was selected as the network infrastructure that connects the server and the sensors. This was chosen because the network in the forest is always very low due to issue of proximity to network mast in the forest, especially in the core forest that is left untouched for over 10 years.

The system consists of the sensors mounted on ESP 32 to garner real time data from the forest environment as seen in Figure 2. The system was further divided into four major units. It comprises of three units acquiring data and sending it to a unit that later transmit it to a remote system data base. Each node was battery powered and has solar panel for consistent power supply for the system to gather data both day and night.

This stage fulfilled the first objective of the research. The images gotten from the camera was analysed on YOLOv8 Ultralytics; The YOLOv8 was initially trained with fire and non-fire images gotten from online sources to train the system as seen in the system block diagram in Figure 3.

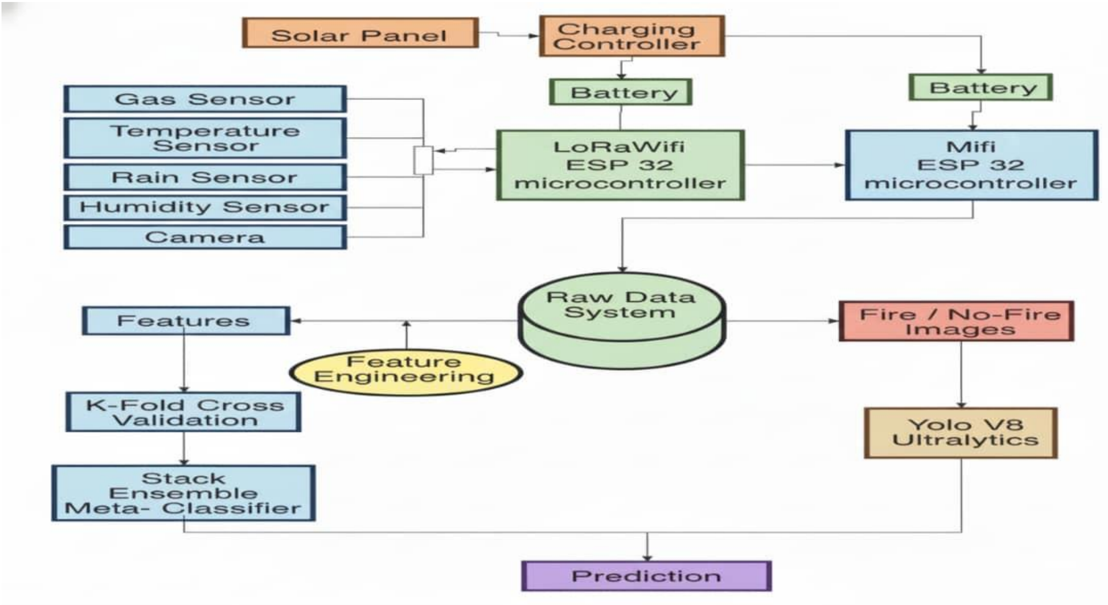


Figure 1: System Framework

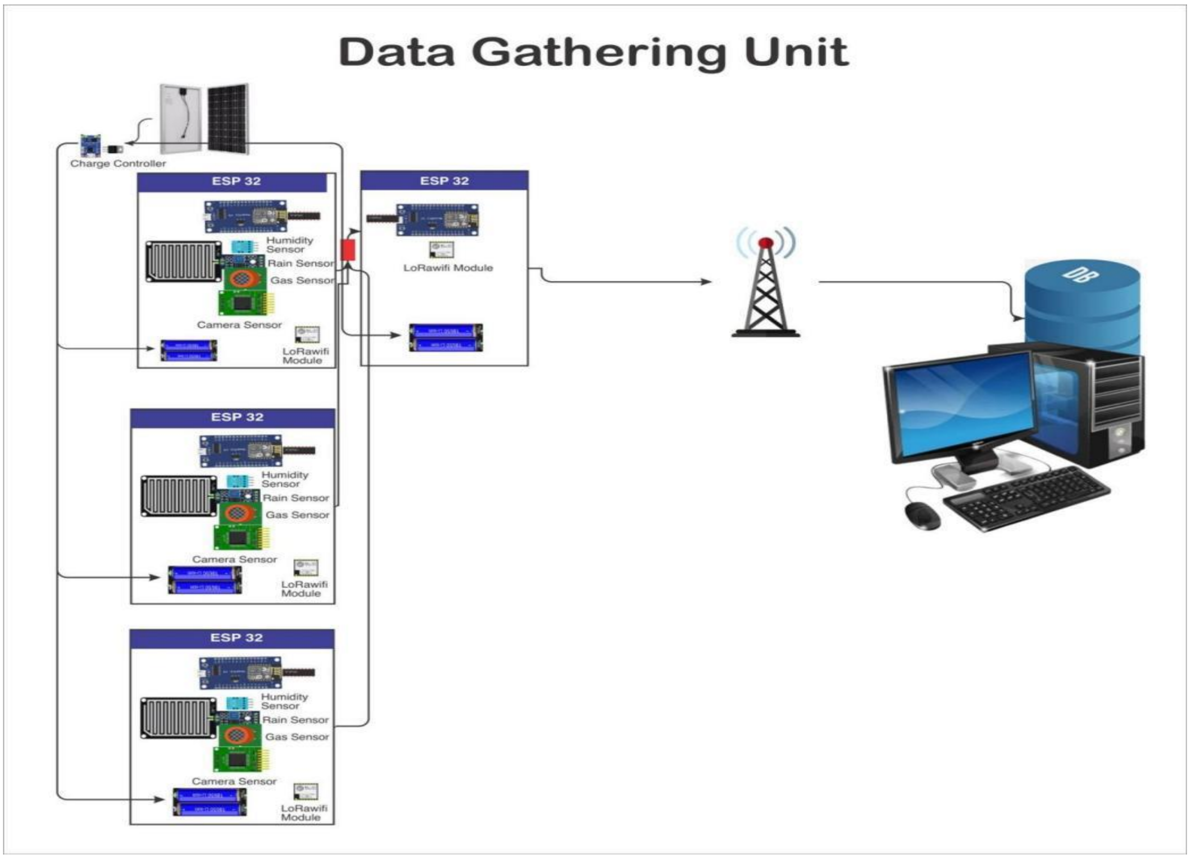


Figure 2: Data gathering using sensors and camera with ESP 32

The output is further combined with the prediction from Stack ensembles meta-classifier to make an improved prediction system about fire incidence in the forest environment. Stacking is a meta-learning technique that combines the predictions of multiple base classifiers using a meta-classifier. Stack ensemble meta-classifier is the fourth phase of the research, the meta-classifiers from Figure 3 are trained on a new datasets that consists of the outputs of the base classifiers as features and the original labels as targets.

It improved the accuracy and diversity of the ensemble model by learning how to optimally combine the base classifiers from fourth phase of the research; The datasets from k-fold cross validation was used on low classifiers such as Random forest, Support Vector Machine, K-Nearest Neighbour, XGBoost and Gradient Boosting.

This setup ensures seamless data flow from the field to decision-making platforms without relying on traditional connectivity infrastructure. The interface of image detection software built on YOLOv8 typically features a streamlined, user-friendly design that made uploading of images or video streams seamless and view real-time detection results with bounding boxes, class labels and confidence scores.

4 Implementation and Model Validation

4.1 Integration of ESP 32 Micro-controller sand LoRa WiFi

The ESP32 microcontroller was integrated with a LoRa WiFi module to establish a robust, long-range communication system for transmitting and receiving sensor data within forest environments. This setup ensures reliable wireless connectivity. between multiple sensing nodes without dependence on conventional network infrastructure. The ESP32 was connected with LoRa WiFi to a suite of environmental sensors including temperature, humidity, smoke/gas, soil moisture and precipitation sensors as illustrated in Figure 4 to maintain continuous operation.

After collecting sensor readings, the LoRa module encodes the data into packets and transmits it via long-range radio frequencies, enabling stable communication across several kilometers even in remote and infrastructure-sparse forest zones. On the receiving side, an additional ESP32 microcontroller equipped with a LoRa WiFi module was deployed to intercept and decode the transmitted sensor signals.

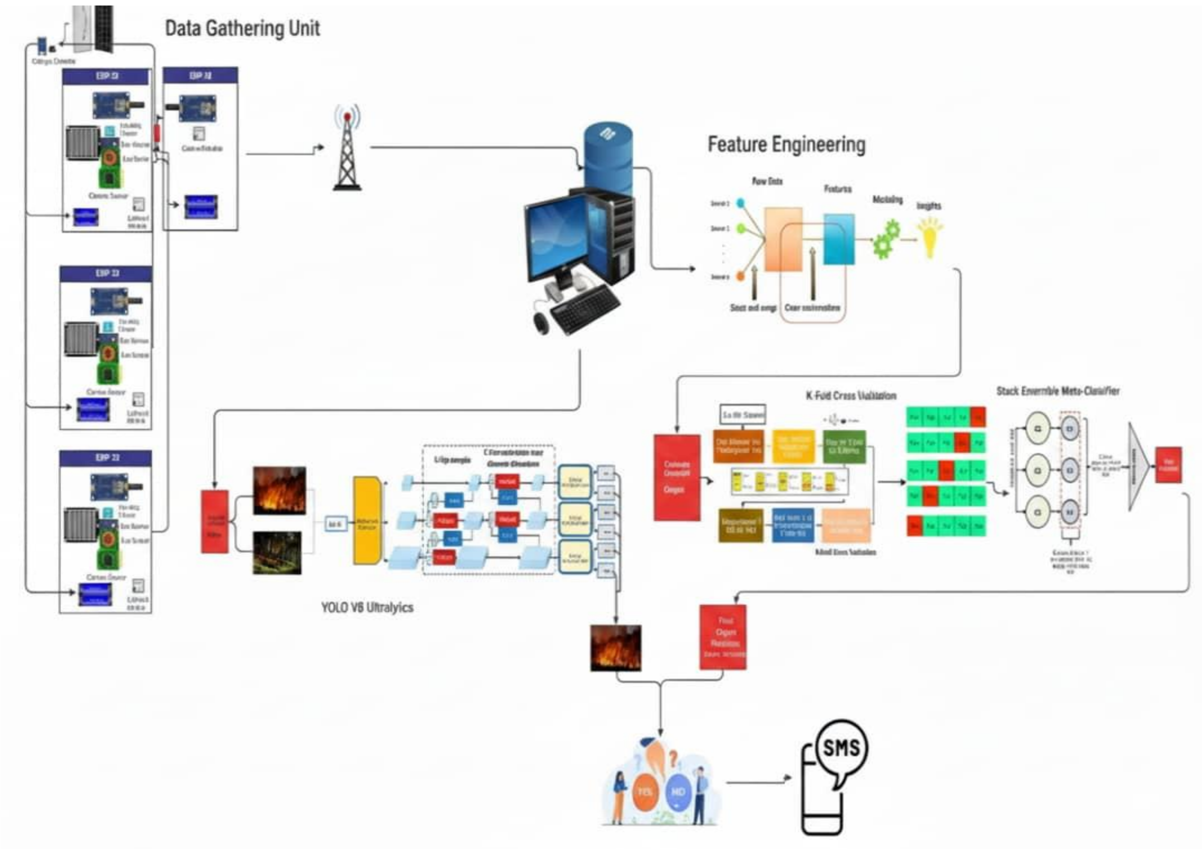


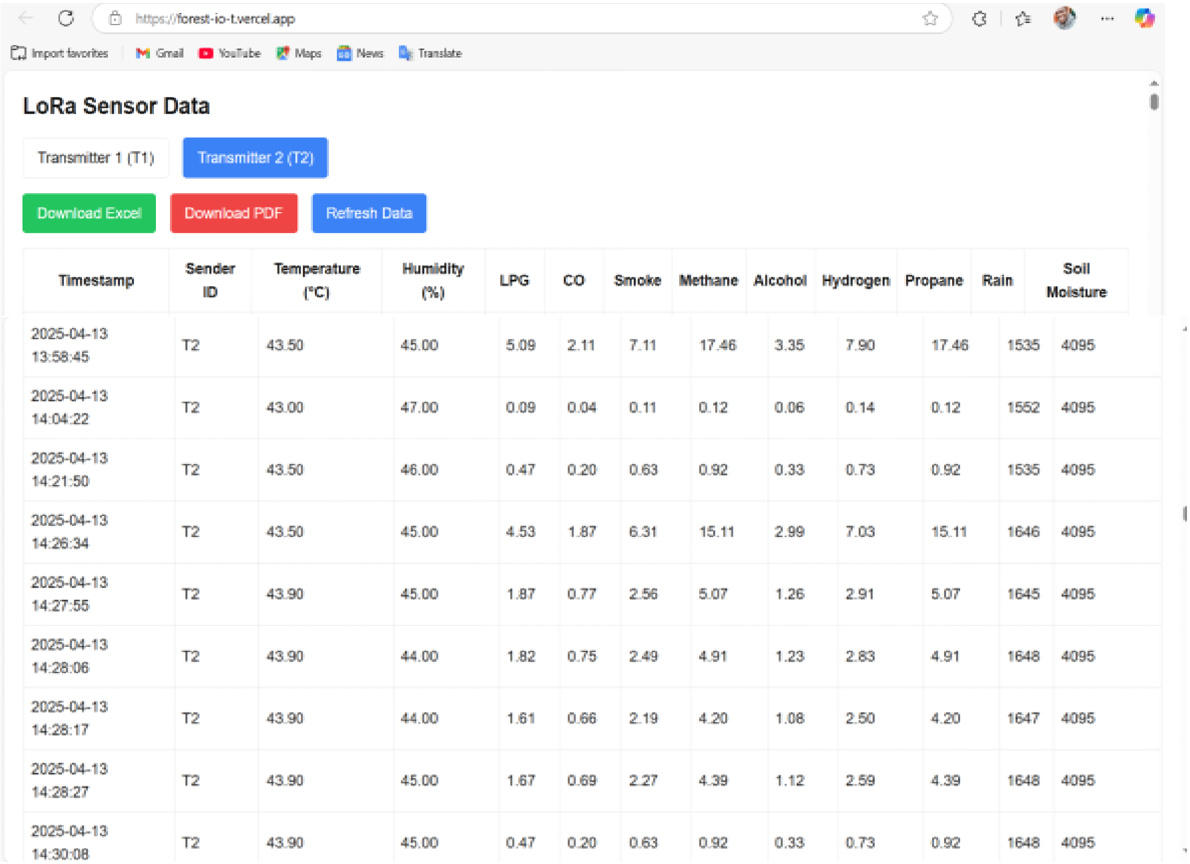
Figure 3: Block Diagram for Intelligent Forest Fire Prediction System (IFFPS)

Once decoded, the data is relayed wirelessly via LoRa to a nearby system or Android device for further processing. The incoming information was then stored locally and rendered through a user-friendly interface, enabling real-time remote monitoring and analytical review of forest conditions.

Figure 4: Components of Forest Data Capturing Device

The setup enabled seamless integration of YOLOv8's high-speed detection capabilities into responsive web application that is accessible for both technical and non-technical users. The fire detection result interface in YOLOv8-based object detection software displays real-time visual feedback in Figure 5.1 and Figure 5.2, with bounding boxes around detected fire regions, annotated with class labels and confidence scores.

The ROC curve (Receiver Operating Characteristic) in Figure 5.3 was used for evaluating binary classification performance in distinguishing between object presence and absence. It plots the True Positive Rate (Recall) against the False Positive Rate across various confidence thresholds in Figure 5,4 which reveals how well the model balances sensitivity and specificity. ROC curves was implemented by extracting prediction scores.



Timestamp	Sender ID	Temperature (°C)	Humidity (%)	LPG	CO	Smoke	Methane	Alcohol	Hydrogen	Propane	Rain	Soil Moisture
2025-04-13 13:58:45	T2	43.50	45.00	5.09	2.11	7.11	17.46	3.35	7.90	17.46	1535	4095
2025-04-13 14:04:22	T2	43.00	47.00	0.09	0.04	0.11	0.12	0.06	0.14	0.12	1552	4095
2025-04-13 14:21:50	T2	43.50	46.00	0.47	0.20	0.63	0.92	0.33	0.73	0.92	1535	4095
2025-04-13 14:26:34	T2	43.50	45.00	4.53	1.87	6.31	15.11	2.99	7.03	15.11	1646	4095
2025-04-13 14:27:55	T2	43.90	45.00	1.87	0.77	2.56	5.07	1.26	2.91	5.07	1645	4095
2025-04-13 14:28:06	T2	43.90	44.00	1.82	0.75	2.49	4.91	1.23	2.83	4.91	1648	4095
2025-04-13 14:28:17	T2	43.90	44.00	1.61	0.66	2.19	4.20	1.08	2.50	4.20	1647	4095
2025-04-13 14:28:27	T2	43.90	45.00	1.67	0.69	2.27	4.39	1.12	2.59	4.39	1648	4095
2025-04-13 14:30:08	T2	43.90	45.00	0.47	0.20	0.63	0.92	0.33	0.73	0.92	1648	4095

Figure 5: Data from Forest Data Capturing Device on Mobile Device

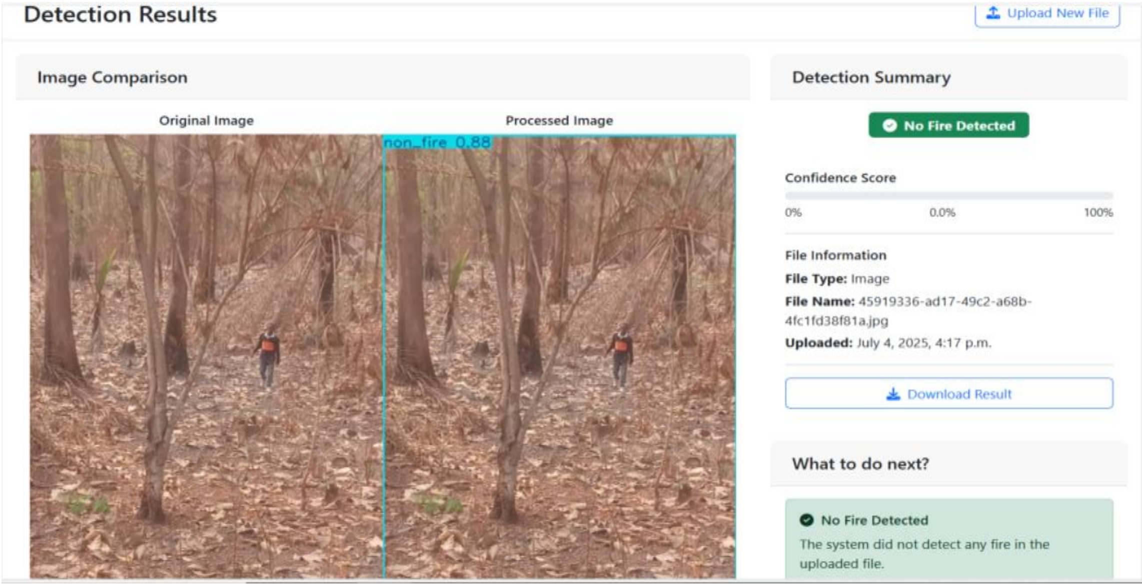


Figure 5.1 : Non-Fire Detection Result Interface

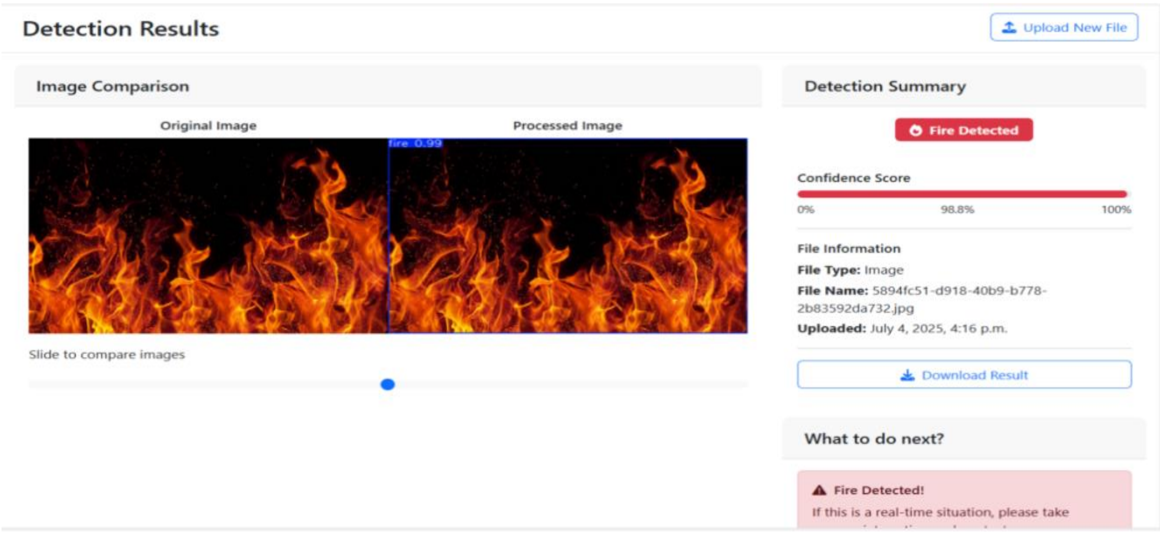


Figure 5.2 : Fire Detection Result Interface

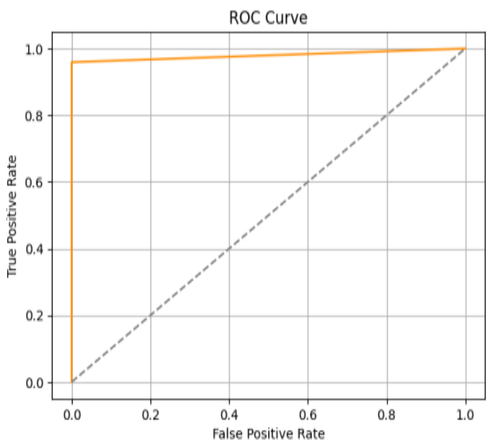


Figure 5.3 : ROC Curve

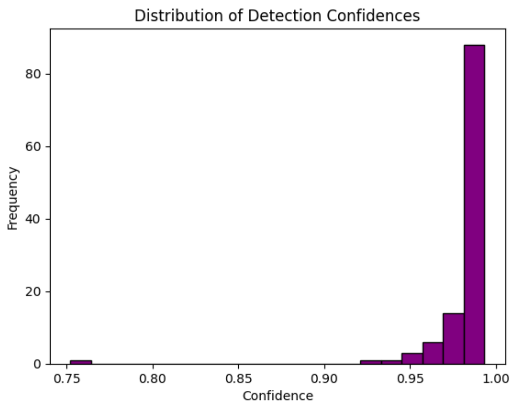


Figure 5.4 Distribution of Detection Confidence

The uploaded images or stream video and the interface overlays detection results directly onto the media, allowing for immediate interpretation of accurate fire identification for emergency response and safety monitoring. The visualization helped in identifying optimal threshold settings and assessed model calibration. The software has an interactive drag-and-drop upload zones, threshold sliders for adjusting detection sensitivity and toggles for displaying class-specific results. The system has an email notifications function as a vital component within AI-driven forest fire detection frameworks, facilitating timely and targeted communication. Upon identifying fire-related anomalies, the system autonomously triggers and dispatches alert messages to designated forest management personnel.

The reporting stage of the forest fire detection system interface distinguishes between fire and non-fire scenarios through annotated image outputs and sensor summaries. The fire interface displays real-time alerts with bounding boxes around detected flames or smoke (via YOLOv8), accompanied by sensor anomalies and automated email logs as seen in Figures 5.6 In contrast, the non-fire interface presents normal environmental conditions, showing stable sensor readings and unflagged image frames to confirm system integrity. This dual-interface design enhances interpretability, supports decision-making, and provides forest administrators with clear visual and data-driven evidence for both active threats and routine monitoring. This automated notification mechanism in Figure 5.5, enhances situational awareness and supports rapid response coordination in wildfire scenarios.

5 Discussion of Results

The classification results reveal a clear hierarchy of predictive power, with tree-based ensemble models acting as the undisputed heavyweights of this dataset. Random Forest, XGBoost, and Gradient Boosting form an elite trio at the summit, each achieving a near-flawless 98% overall accuracy and demonstrating an exceptional ability to balance precision and recall across both classes without breaking a sweat Gradient Boosting even achieved a perfect 100% recall for class 1. Sitting just below this top tier is the Support Vector Machine (SVM), which acts as a highly reliable runner-up with 96% accuracy, showing fantastic sensitivity to class 1 (99% recall) but struggling just slightly more with false positives in Table 1, than the ensemble methods. Finally, K-Nearest Neighbors (KNN) lags behind as the weakest link at 93% accuracy; while it easily identifies class 0, it noticeably stumbles when trying to pinpoint class 1, dropping to an 86% recall and highlighting its geometric limitations when faced with the complex data patterns that the boosting algorithms sliced through effortlessly.

Figure 5.5: Email notification for fire alert

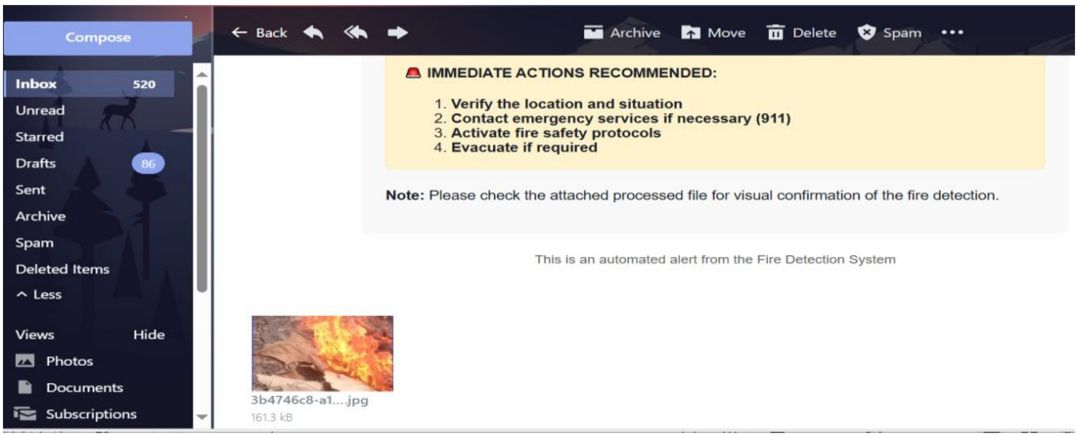


Figure 5.6: Email alert interface

Table1: Base Classifiers Results

Model		Precision (%)	Recall (%)	F1- score (%)
Random Forest	1	97	99	98
	0	99	97	98
	accuracy			98
	Macro avg	98	98	98
	Weighted avg	98	98	98
SVM	1	94	99	96
	0	99	94	96
	accuracy			96
	Macro avg	96	96	96
	Weighted avg	96	96	96
KNN	1	88	86	93
	0	99	99	92
	accuracy			93
	Macro avg	94	93	93
	Weighted avg	94	93	93
XGBoost	1	96	99	98
	0	99	96	98
	accuracy			98
	Macro avg	98	98	98
	Weighted avg	98	98	98
Gradient Boosting	1	96	100	98
	0	100	95	97
	accuracy			98
	Macro avg	98	98	98
	Weighted avg	98	98	98

The classification report displays an exceptionally strong model with an overall accuracy of 98% across a dataset of 114 instances. The most critical metric for safety applications is the perfect recall of 1.00 for the fire class, meaning the model successfully detected every actual fire without a single false negative. While it did generate a minimal number of false positives evidenced by the slightly lower fire class precision of 0.97 and the non_fire recall of 0.96 this is an ideal trade-off for a hazard detection system where missing a real fire is much worse than occasionally triggering a false alarm. Overall, the balanced F1-scores of 0.98 in Figure 6, confirm that the model is highly reliable, effectively minimizing missed detections while maintaining an incredibly high rate of correct predictions.

Classification Report:

	precision	recall	f1-score	support
fire	0.97	1.00	0.98	65
non_fire	1.00	0.96	0.98	49
accuracy			0.98	114
macro avg	0.99	0.98	0.98	114
weighted avg	0.98	0.98	0.98	114

Figure 6: Classification Report

The evaluation of the YOLOv8 model for fire detection demonstrates state-of-the-art performance, achieving a macro-averaged F1-score of 0.98 and an overall accuracy of 98%. Notably, the model recorded a perfect recall rate of 1.00 for the positive "fire" class, an essential metric for safety-critical early warning systems where minimizing false negatives is paramount. These results significantly outperform standard baseline YOLOv8 implementations reported in contemporary literature, which typically yield F1-scores and recall rates in the low-to-mid 90th percentile due to challenges with small-scale flames and environmental occlusion. While the current findings underscore a highly optimized architecture capable of flawless sensitivity on the 114-instance test set, subsequent validation against larger, more heterogeneous datasets containing complex environmental artifacts is recommended to confirm the model's robust generalization in unstructured, real-world deployment scenarios.

The integration of IoT sensor arrays with the YOLOv8 object detection framework forms a robust, multi-modal system for proactive forest fire prediction and response. Distributed environmental sensors monitor key parameters such as temperature, humidity, and gas concentrations, transmitting data via low-power protocols to an edge gateway. When anomalies are detected, the system activates a high-resolution camera to capture imagery, which is analyzed in real time by YOLOv8 to identify fire and smoke signatures with high accuracy. This dual-layered approach combines continuous sensor surveillance with deep learning-based visual confirmation enhances situational awareness, reduces false positives, and proves especially effective in remote or high-risk forest zones. The system also supports rapid emergency response through automated email alerts containing annotated images, enabling swift action to mitigate wildfire threats and protect surrounding ecosystems.

5.1 Conclusion

The integration of IoT-based environmental monitoring with AI-powered image recognition marks a transformative advancement in predictive forest fire management. By combining continuous sensor data collection with high-precision visual analysis using models like YOLOv8, the system offers both proactive detection and rapid response capabilities. Unlike traditional methods such as satellite imaging and manual patrols which are often hindered by delays and limited coverage, the IoT-AI hybrid enables real-time surveillance, autonomous edge processing and remote alert delivery. This synergy improves detection accuracy, enhances scalability and reduces operational costs, making it a vital tool for modern wildfire prevention and control. To enhance the operational effectiveness of the forest fire detection system, expanding the IoT sensor network into high-risk zones is essential, complemented by drone-assisted aerial surveillance for real-time imagery in inaccessible terrain. Integrating edge computing through AI-enabled microprocessors at sensor nodes enables faster, localized decision-making and reduces latency, especially in low-connectivity areas. Maintaining detection accuracy also requires periodic retraining of the YOLOv8 model using diverse datasets, including synthetic fire scenarios, to improve robustness and minimize false positives. Institutional support is equally vital, involving standardized emergency protocols and embedding the system within national or regional disaster management frameworks to ensure coordinated and timely responses to fire alerts.

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