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Framework for Development of a Multimodal Artificial Intelligence Based Forest Fire Prediction

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ABSTRACT

This research proposes a multimodal Artificial Intelligence framework for forest fire prediction, combining sensor-driven meta-classification with advanced image analysis using YOLOv8. The system integrates real-time environmental data captured via a custom IoT device equipped with ESP32 and LoRaWiFi from fire-prone regions in southwestern Nigeria, alongside visual inputs from ground cameras and autonomous drones. Sensor data is processed through a layered ensemble of machine learning algorithms, while YOLOv8 identifies visual fire cues such as smoke and flames. A decision-level fusion mechanism merges both data streams to deliver high-accuracy predictions, minimize false alarms, and enable rapid, autonomous alerts. The framework demonstrates strong generalization, reliability, and scalability, making it a promising solution for low-resource, real-time forest fire monitoring and emergency response.

Keywords: Framework, Development, Multimodal Artificial Intelligence, Forest Fire, Sensors Prediction,LoRaWiFi, YOLOV8 Image Analysis,

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1. INTRODUCTION

Sensor based fire prediction has gained prominence in Internet of Things (IoT) as a means of fire mitigation technique. The IoT refers to a network of physical objects or devices embedded with sensors, software, and connectivity to enable the collection and exchange of data over the Internet (Hakima, 2021).

The Internet of Things (IoT) is a network of connected computing devices, mechanical and digital machinery, items, animals, or people that may exchange data across a network without requiring human-to-human or human-to-computer interaction (Alexander, 2022). Sensor-based and vision-based smoke detection systems have garnered a lot of interest in the research community among these techniques.

An Intelligent Forest system is introduced in this study by combining IoT, cloud computing, and web application services to create a smart forest. Using ESP 32 microcontroller platform, intelligence is integrated into the sensor. ESP 32 microcontrollers are equipped with LoRaWi-Fi technology for networking smart things. Interacting with smart things becomes easier with Cloud computing, and access to smart things is simplified from anywhere which improves the efficiency of data processing. Using this design, services that monitor, measure, and control home conditions, appliances, and access have been successfully explained. In real time, the design keeps all readings updated and appears efficient and secure (Murad, *et al.,* 2021). The Internet of Things (IoT)-based forest automation system is intended to create a connected and intelligent forest environment which enables the automation, control, and monitoring of several forest conditions. The intelligent forest automation system improves the security, safety of wildlife and huge economic resources within the forest ecosystem by integrating IoT technology.

Wild fire is a natural mechanism of a self-regulation of terrestrial ecosystems and anthropic activities which may alter natural regimes, leading to a decrease in their capacity to reduce the intensity, magnitude and spread of forest fires (Depietri, and Orenstein, 2019). The frequency and intensity of wildfire patterns contribute to increase in the rates of Greenhouse Gas (GHG) emissions, loss of land cover, acceleration of erosive processes and a higher pressure on biodiversity (Armenteras, *et, al*., 2022). Unlike other types of hazards, a wildfire has multiple causative events and for it to occur, certain conditions related to the combustible biomass, the ignition event and the spreading of fire must be met.

Machine learning (ML) plays a significant role in predicting and mitigating forest fires which is crucial for environmental conservation and public safety. Real-time weather information such as temperature, humidity, wind speed, Rainfall and smoke are garnered through sensors which helps in understanding fire risk. Historical data on past forest fires aids in training ML models. Relevant features were extracted from the weather data and additional features like distance to water bodies, elevation, and vegetation density also help the model prediction. Data pre-processing was carried out during the formation of a standardized dataset for the analysis. During pre-processing, raw data were cleaned, transformed, and organized to ensure consistency and suitability for subsequent analysis. By addressing missing values, outliers, and other data quality issues, reliable dataset emerged for further exploration and modeling. (Sonia and Clara , 2022).

Ensemble methods was applied to both classification and regression problems, and they have been proven to be effective in improving accuracy, reducing overfitting, and enhancing the model's generalization ability. Stacking method was employed in this study were 5 base classifiers were trained to achieve optimum accuracy and stacking combines the predictions of multiple models by training a meta-model (also known as a blender or aggregator) on the outputs of the base models.

The base models make predictions on the training data, and these predictions, along with the original features, are used as input to the meta-model, which generates the final prediction. Stacking allows the meta-model to learn how to best combine the predictions of the base models.

2. RELATED WORKS

Internet of Things (IoT) technology allows for the remote management and configuration of all things (devices), including Cyber-Physical Systems (CPS) that use telecommunications to connect the physical and digital worlds. The development of Intelligent Forest was facilitated by the integration of IoT into Forest Automation (F.A.) systems. Systems operated manually, such as those for heat, humidity, rain, smoke can be observed and managed remotely in smart forest (Alsoufi, *et. al*., 2021).

YOLO V8 Ultralytic is part of the YOLO (You Only Look Once) family of models, which are known for their real-time object detection capabilities and unlike traditional object detection methods that involve multiple stages will be used to processes the entire image in one pass it was choosing based on improvements in its architecture, training techniques, and performance. YOLOv8 model was pre-trained to identify the presence of fire and smoke in individual video frames and it tracks these detections across subsequent frames, allowing for real-time monitoring from dataset containing annotated fire and smoke images for training (Saydirasulovich, *et.al*., 2023).

The multi-sensor data fusion technique integrates data from multiple sensor nodes and transmits the combined data from Figure 1.0(a,b,c,and d) to the base station, reducing communication overhead and saving sensor energy. However, to use a WSN to detect a fire in its early stages, existing environmental factors such as temperature, relative humidity, wind speed, gas detection, and so on must be known (Verma, and Singh, 2020). Network architecture is the design and structure of a network that defines how the components and devices are interconnected and communicate with each other. Network architecture can affect the performance, reliability, security, and scalability of a network. There are different types of network architectures, such as client-server, peer-to-peer, cloud computing, software-defined networking, and internet of things (Kaliyamurthy, *et. al*., 2021).

When a large number of sensor nodes are deployed in a large area to co-operatively monitor a physical environment, the networking of this sensor node is equally important. A sensor node in a WSN not only communicates with other sensor nodes but also with a Base Station (BS) using wireless communication. The base station sends commands to the sensor nodes and the sensor node performs the task by collaborating.

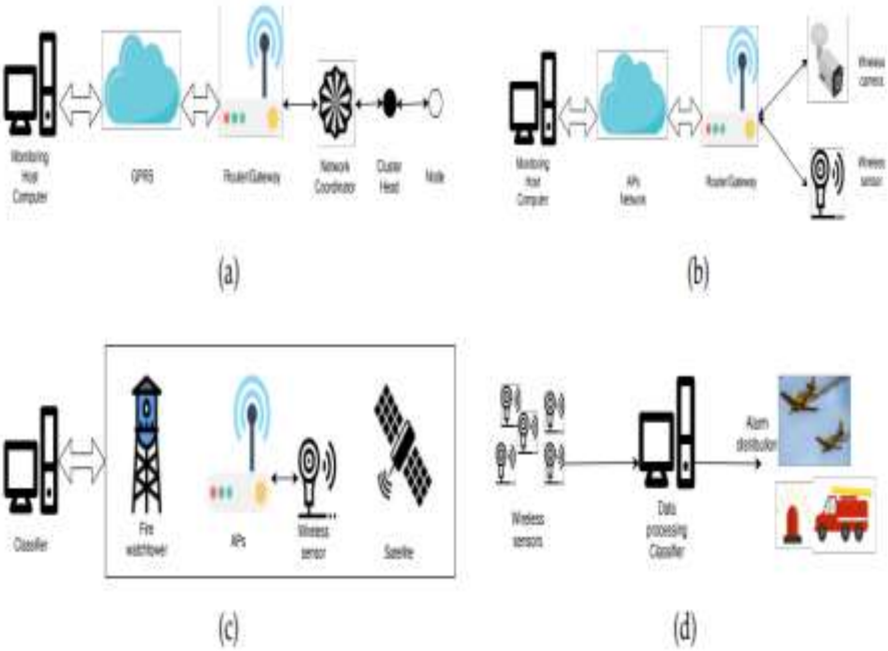

Figure 1: Different topologies of wireless sensor network architectures.
(a) Topology based on dense distribution of environmental sensors; (b) Topology based on dense distribution of wireless sensors in addition to wireless cameras; (c) Classifier based on the combination of different inputs; (d) Data classifier based on sensor values and alert management. (Carta, *et. al*., 2023).

3. METHODOLOGY FRAMEWORK

The research is in two major phases. A theoretical and a practical phase. The theoretical phases are based on a pilot study where the study navigated through data gathering concerns regarding IoT devices and found appropriate research scope to support the objective of the study. The practical phase is to propose a framework which can fulfil the study's objectives and develop it with the help of appropriate tools, sensors, camera and microcontroller boards.

The framework was designed in the practical phase of the overall project functionality for data gathering sensors and other hardwares from Figure 3.1. 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. Three of this unit was 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 transmit 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 ESP 32 development board has analog pins and digital pins, with built-in Wi-Fi embedded, which connect to a server. Then Intelligent Forest System was accessed remotely from any PC or mobile handheld device connected to the internet with an appropriate web browser through real server IP (Internet IP). Blynk IoT is the mobile application used to control the system.

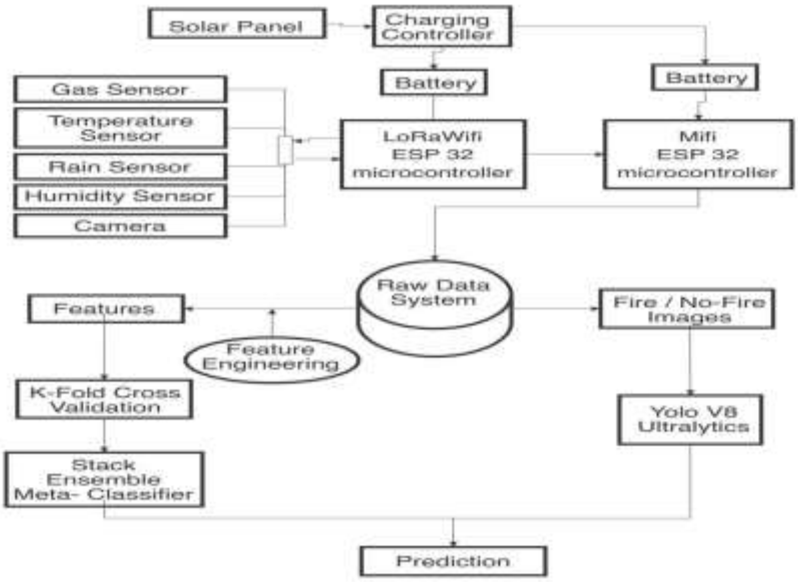

Figure 2: The System Frame Work

The system consists of a Microcontrollers, LoRaWiFi, MiFi, Routers, Camera and Sensors. The first phase of the system consists of the sensors mounted on ESP 32 to garner real time data from the forest environment as seen in Figure 2.1

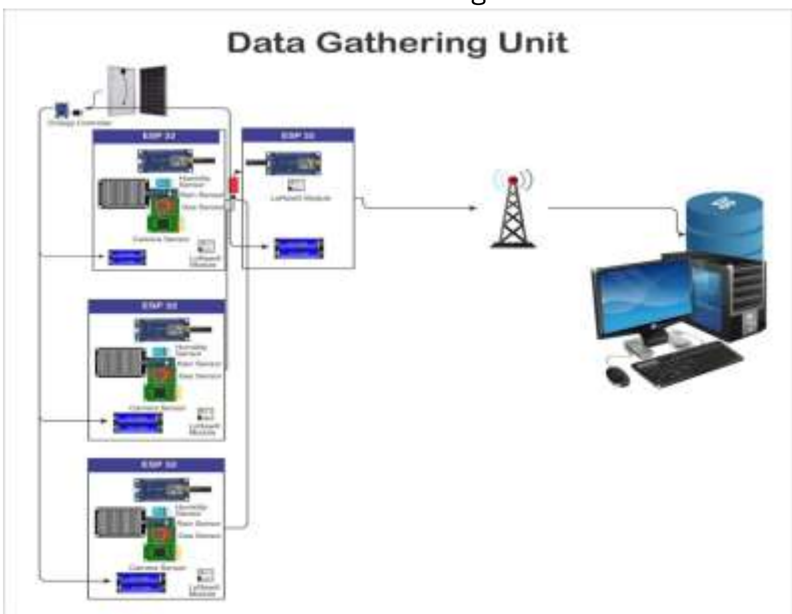

Figure 2.1 Data Gathering Using Sensors and Camera with ESP 32

The K-fold cross validation for evaluating the performance and generalization of the model or algorithm involves splitting the data into **k** subsets or folds, and then using one fold as the **test set** and the remaining **k-1** folds as the **training set**. This process is repeated **k** times, each time using a different fold as the test set. The average of the **k** test results is then used as the final estimate of the model's performance. K-fold cross validation from Figure 2.2 can help reduce the **variance** and **bias** of the model, and also make use of the entire data set for both training and testing.

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 2.3 are trained on a new dataset that consists of the outputs of the base classifiers as features and the original labels as targets. The accuracy and diversity of the ensemble model was improved by learning how to optimally combine the base classifiers from fourth phase of the research; The dataset from k-fold cross validation will be used on low classifiers such as Random forest, Support Vector Machine, Naïve based, Decision Tree and Logistic regression.

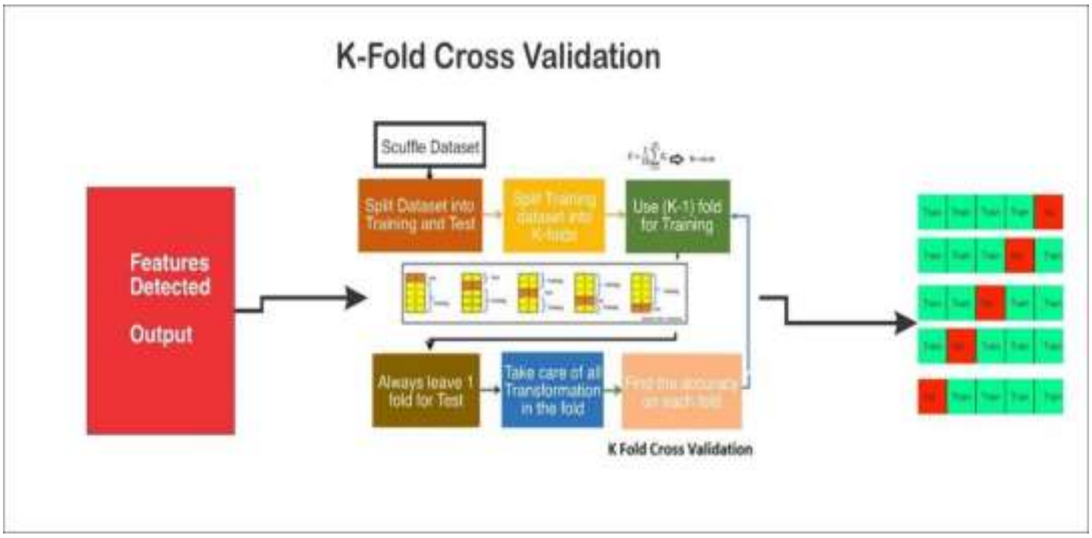

Figure 2.2: K-Fold Cross Validation

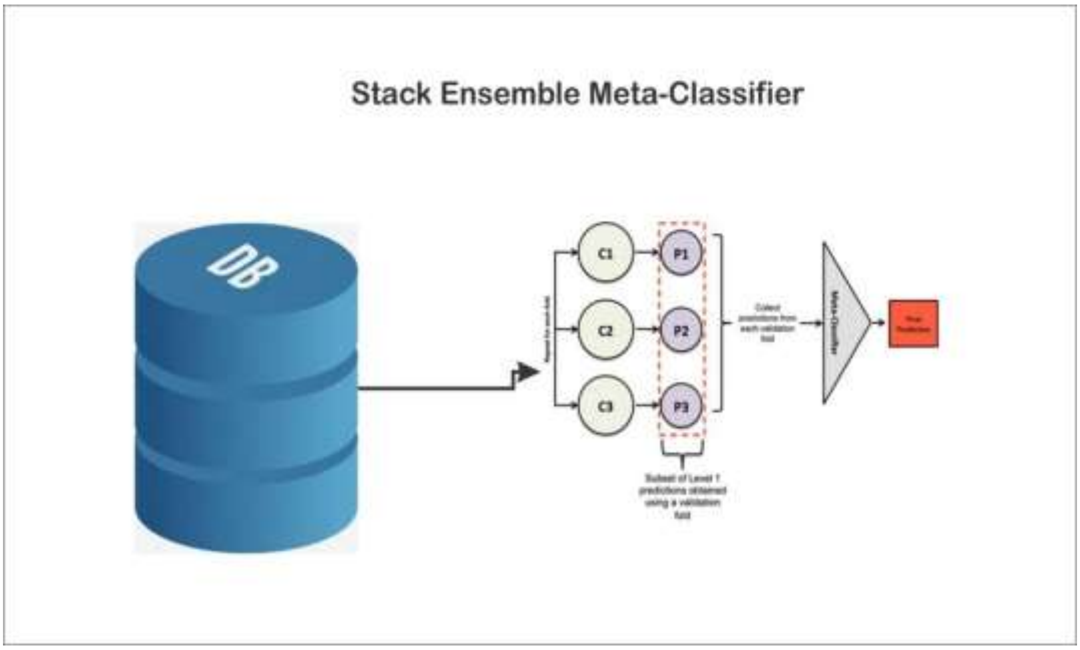

Figure 2.3: Stack ensemble Meta-Classifier

The images gotten from the camera will be analyzed on YOLOv8 Ultralytics; The YOLOv8 will be initially trained with fire and non-fire images gotten from online sources to train the system. After subjecting the acquired images into YOLOv8 from Figure 2.4, the system gives an output which is either fire or non-fire image. 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.

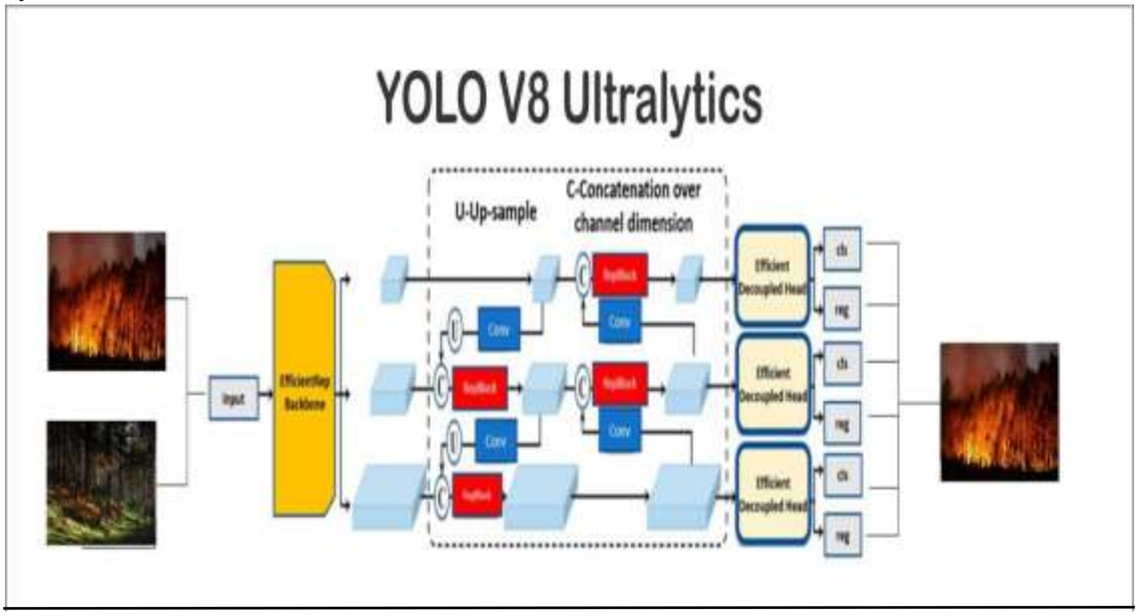

Figure 2.4: YOLOv8 for Image Classifications

4. DISCUSSION

The physical layer consists of the devices that are to be controlled. The sensors to sense the surrounding environmental conditions are also connected to this layer. The data link layer consists of an IoT gateway router (here, we have used ESP 32, Lora WIFI and MiFi as router gateway), a device manager and various communication protocols. This layer links the home appliances to the web server or cloud via Wi-Fi communication. The ESP 32, Lora WIFI will be used as a private server to store the sensor data and sends data to the base station. In this system, ESP 32 falls under the database/server layer.

The proposed system was implemented using ESP 32 by overcoming all the drawbacks of previous existing methods. In this study, all the sensors are connected to the ESP 32 board, from Figure 2.5 and the sensor data will be analyzed using Stack ensemble meta-classifier and results can be seen on smartphones. The ESP 32 is the microcontroller or the main controlling unit of the system.

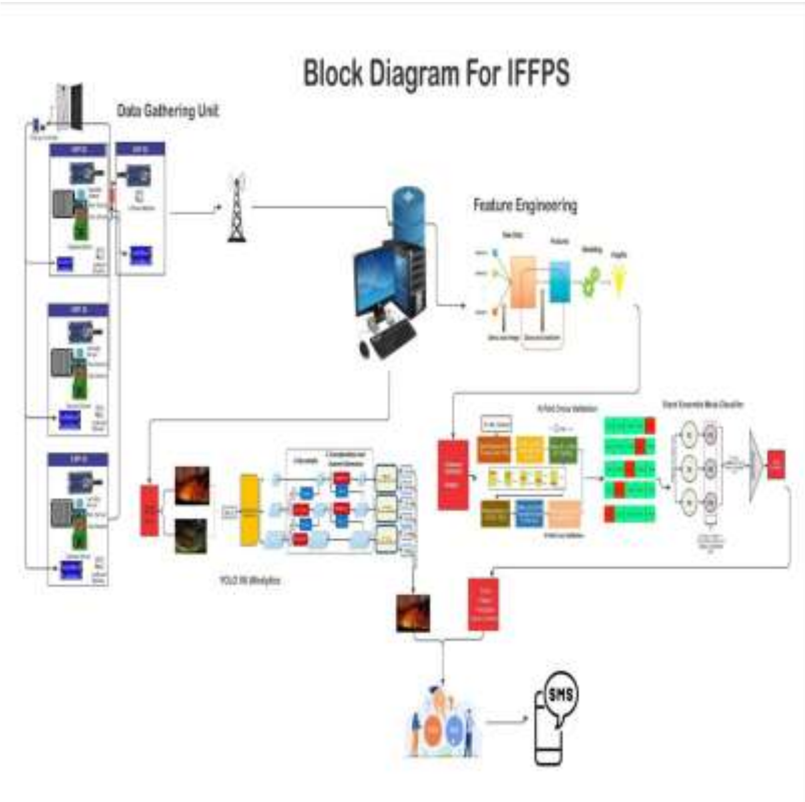

Figure 2.5: Block Diagram of Proposed Intelligent Forest Fire Prediction System (IFFPS)

Blynk IoT Application

Blynk is a digital platform that uses a graphical interface to simplify project creation. Its objective is to facilitate remote monitoring and control of devices through the use of a smartphone app (Kazi and Sayyad, 2024). Blynk's functionality includes storing and visually presenting data with numbers, colors, or graphics, which makes it more approachable for beginners working on Internet of Things. The Blynk application is primarily designed for Internet of Things applications.

Blynk is an app platform for iOS and Android devices that allows controls to the Arduino, Raspberry Pi, and other devices over the Internet. Drag and drop widgets can be used to build a graphic interface for a prototype on a digital dashboard. Besides controlling hardware remotely, it can display sensor data, store and visualize data, and perform many other functions and three major components of Blynk platform are:

i. **Blynk Application:** enables users to use the numerous widgets offers to build fantastic user interfaces for the projects.
ii **Blynk Server** is responsible for all the communications between the smartphone and hardware. It can even be launched on a Raspberry Pi, is open-source, and can readily manage thousands of devices. Users can host a private Blynk server locally or utilize the Blynk Cloud.
iii **Blynk Libraries:** Enable communication with the server and handle all incoming and outgoing commands for all popular hardware platforms.

5. SUMMARY

This paper presents a multimodal AI-based framework for forest fire prediction that integrates real-time sensor data and visual imagery using a meta-classifier and YOLOv8 image analysis. The system employs a custom IoT device to collect environmental metrics from fire-prone areas in southwestern Nigeria, while cameras and drones capture visual indicators of fire. Sensor inputs are processed through an ensemble of machine learning models, and visual data is analyzed using YOLOv8 to detect smoke and flames. A fusion mechanism combines both outputs to enhance prediction accuracy, reduce false alarms, and enable fast, autonomous alerts. The framework proves to be reliable, scalable, and well-suited for low-resource, real-time fire monitoring and emergency response.

6. CONCLUSION

In conclusion, the proposed multimodal Artificial Intelligence framework effectively combines sensor-based meta-classification with YOLOv8 image analysis to deliver accurate and timely forest fire predictions. By integrating heterogeneous data sources and leveraging a decision-level fusion mechanism, the system significantly reduces false positives and enhances situational awareness through autonomous alerts. Its high performance across diverse environmental conditions and scalability in low-resource settings underscores its potential as a reliable tool for real-time forest fire monitoring and emergency response, contributing meaningfully to disaster preparedness and environmental protection efforts.

7. RECOMMENDATION

It is recommended that this multimodal Artificial Intelligence framework be further explored and adapted for broader deployment in other fire-prone regions, given its demonstrated effectiveness in integrating sensor data and image analysis for accurate forest fire prediction. Future research should focus on optimizing the system’s scalability, enhancing drone autonomy, and incorporating additional environmental variables to improve detection under diverse conditions. Collaboration with emergency response agencies and integration into national disaster management systems could significantly enhance real-time monitoring capabilities and reduce the impact of forest fires in low-resource settings.

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