Leveraging IoT and Machine Learning for Next-Generation Forest Fire Detection Systems

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***Abstract*—Forest fires are one of the most unplanned disasters that trigger extreme destructions in the different ecosystems of animals and humans. Early detection coupled with proper measures is very vital in controlling such uncontrolled disasters. The title of this project is "Design and Preliminary Data Acquisition for an AI Enabled Forest Fire Sensing System with IOT: A Study on Model Selection and Sensor Integration" and its aim is to develop a foundational framework for a reliable wild fire detection system using IoT technologies. This project uses a network of sensors including humidity, temperature, and smoke and along with acoustic sensors using an ESP32 microcontroller that maintains the environmental condition monitoring all the time. This development phase is based on data gathering and training for machine learning models in sensor data for potential fire detection. Results of this study will now be used in further improvements and optimizations to ensure the system is robust and scalable. This project takes advantage of the opportunities presented by IoT and machine learning to provide an effective early warning system for forest fires, which could lead to advanced monitoring and response strategies.**

Keywords—IoT (Internet of Things), Data Acquisition, Preliminary Date Collection, Autoencoders, Machine Learning.

I. Introduction

Forest fire (wildfire or a bushfire) is a disaster which is caused by the natural activities or man-made activities occurs in the forest. This is unpredictable, unplanned and uncontrollable disaster. This causes high destruction of vegetation's, collapse the wildlife habitat, loss of animal lives and also affects the forest revenue which influence the economic aspects of the country. The primary cause of the forest fire is that dry conditions (low humidity) and high air temperatures provide an ideal environment for a fire to start. This was brought on by the temperature change that occurred naturally. When an electric spark, cigarette, naked flame, or other source of ignition comes into touch with combustible material, it is one of the man-made causes of forest fires. The Internet of Things, or IoT, refers to a network of connected physical hardware devices that are provided with sensors, software, and other technologies to create incredibly effective gadgets for many applications. This is an advanced technology used in enormous fields to build high-end devices for a fast and effective system to handle crucial data efficiently. Edge Computing is an emerging computer paradigm. It is a distributed computing framework that brings storage of data and computation together for efficient and fast processing. It helps to reduce the latency and bandwidth use. The computing is focused on collecting the data from the source and processing the data in the source itself. The proposed system will be using a combination of two machine learning models called Autoencoders and MFCC (Mel Frequency Cepstral Coefficients). Autoencoders are an advanced deep learning algorithm that is used to learn data encodings in an unsupervised manner. This algorithm is more efficient to train and test the sensor data and predict the results. MFCCs (Mel Frequency Cepstral Coefficients) are feature extraction technique which are widely used in audio and speech processing. This machine learning technique helps to process the surrounding sounds in the forest which are captured by the acoustic sensors and detects the fire crackling sound accurately

II. Literature Survey

Zheng et al. [1] explain the importance of prevention of forest by using SR-net model with high resolution satellite images where the SR-net model is the combination of Convolutional Neural Network (CNN) and lightweight Vision Transformers (ViT). By training this model in unique dataset with 4,000 satellite remote sensing images and it provides the accuracy of 96.9%. But this SR-net model is well-suited for applications in remote sensing with limited datasets.

Nakau et al. [2] it mainly addresses the forest fires in boreal regions like Alaska and Siberia with MODIS satellite imagery for detecting forest fires. The data covers a wide geographic area centered around Yakutsk in West Siberia and Alaska and found significant differences in detection rates depending on the observation source and highlighted the limitations of satellite-based detection in certain conditions. The integration of ground and aerial observations with satellite data is crucial for effective forest fire management. But this project is limited to specific geographic area and also detection sources won't be available at the right time.

Verma et al. [3] introduced an Intelligent Framework Using IoT enabled WSNs for Wildfire Detection. This proposed solution called the Sleep scheduling-based Energy Optimized Framework (SEOF) mainly uses strategies that are Cluster Head (CH) selection using the Tunicate Swarm Algorithm (TSA) and a sleep scheduling mechanism for sensor nodes. The SEOF framework is implemented with the help of MATLAB. This methodology is not helpful for detecting the forest fire efficiently it thoroughly focusing on the energy efficient network in hostile environments.

Jang et al. [4] addresses the detection and monitoring of Forest Fires with a system which is implemented as a machine learning-combined approach to detect small to large-scale forest fires. The methodology followed by this study is threshold-based algorithms-based machine approach. The author used random forest (RF) model and then processes the pixels to remove false alarms. The model demonstrated an overall accuracy of about 99.16%. But this algorithm is applicable for certain region with specific climatic conditions.

Ghali et al. [5] proposes ensemble learning method combining EfficientNet-B5 and DenseNet-201 models for wildfire detection and classification. The proposed ensemble method using EfficientNet-B5 and DenseNet-201 achieved an accuracy of 85.12% but the UAV is not efficient under certain environmental factors.

Naoto Maeda and Hideyuki Tonooka [6] implemented modified algorithm uses a random forest classifier that incorporates solar zenith angle, AHI band values, contextual parameters, and meteorological data. This model gives the accuracy of 92.06% with all the parameters involved. Although the dataset used in this system is not effectively determining the forest fires.

Sandra Treneska and Biljana Risteska Stojkoska [7] proposes Unmanned Aerial Vehicles (UAVs) with using Transfer learning to enhance the detection of forest fire. This uses peculiar dataset called FLAME (Fire Luminosity Airborne-based Machine learning Evaluation) dataset consists of aerial images captured during prescribed burns in Northern Arizona. The transfer learning algorithm uses pre-trained models like VGG16, VGG19, ResNet50, InceptionV3, Xception for accurate detection with the given dataset. This system results with the highest accuracy of 88% from ResNet50 model and followed closely by InceptionV3 at 87%.

Fouda et al. [8] proposed switching the models from basic machine learning model to advanced deep learning CNN model. The hyperparameters are tuned using TOPIS method. The proposed approach outperforms individual baseline models and offers a viable solution for real-time fire detection on resource-constrained UAVs.

Almeida et al. [9] comes forward with a new light-weight CNN model for real-time video for the detection of fire and smoke in forests. This CNN model is consisting of 2 convolutional layers with 32 filters for analyzing the images captured in real - time. The model reached the accuracy of 98.97% and an F1 score of 95.77%

Varun et al. [10] addresses the integration of IoT and Machine Learning for Enhanced Forest Fire Detection and Temperature Monitoring. The proposed system integrates IoT devices, advanced sensors, machine learning algorithms, and fog computing concepts to provide a reliable and effective wild fire detection and prevention system. The technology aims to transform the field of forest fire monitoring by providing real-time data processing, accurate predictions, and prompt notifications, leading to improved environmental protection and public safety.

III. METHODOLOGY

Our method includes the collection of data from key sensors such as DHT22 (for temperature or humidity), MQ-2 Gas sensor (for smoke), and MAX4466 Microphone Amplifier (for acoustic detection). The collected data will be used for model selection, training, and anomaly detection for the forest fires. These data will be essential for the detection of forest fires.

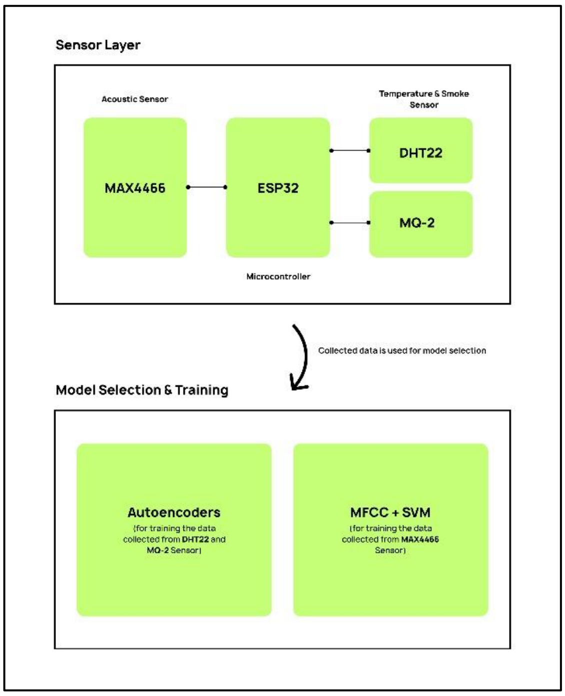

Fig.1. System Architecture

Role of ESP32 Microcontroller:

The ESP32 is chosen for the following reasons:

Fig.2. ESP232 Microcontroller

Low Power Consumption - power efficiency is critical for this kind of application where the system should perform its function for extended periods with minimum power consumption. Built-in Wi-Fi and Bluetooth - wireless communication is an important part of this system where the sensor data has to be transferred elsewhere for processing.
Multiple I/O Pins - ESP32 contains multiple GPIO Pins which plays an important role in connecting several sensors to the microcontroller. Sensors Overview and Purpose:
The system relies on three key sensors to monitor the environmental factors:

DHT22 (Temperature and Humidity Sensor)

Fig.3. DHT22 (Temperature and Humidity Sensor)

This sensor measures and gives real time data in terms of both temperature and humidity, important elements in assessing a situation that risks a fire. High temperatures with low humidity levels are perfect conditions to ignite a fire and have them spread. The DHT22 has a measuring scale for temperature in degrees Celsius and is accurate in stating the percentage humidity level.
Why This Sensor? DHT22 is used for reliability and accuracy under extreme conditions of forest, where temperature and humidity can vary. With the capability to observe temperature and humidity within low power consumption, this is one good sensor to be used with this system.

MQ-2 (Smoke and Gas Detection Sensor)

Fig.4. MQ-2 (Smoke and Gas Detection Sensor)

MQ-2 sensor detects the presence of smoke and flammable gases like methane, propane, and LPG which are evident signs of fire. It works on the principle whereby it outputs an analog signal that is proportional to the concentration of those gases. Why this sensor? As soon as a fire breakout occurs, the concentration of smoke and gases will be increased to a much higher level. The MQ-2 sensor is very responsive to these changes, and it provides real-time feed-back about dangerous gases, which in turn helps the sensor mark the fires as early as possible. This MQ-2 sensor is integrated with fire detection systems and it is widely used due to its high efficiency and cost effectiveness.

MAX4466 (Acoustic Sensor for Sound Detection)

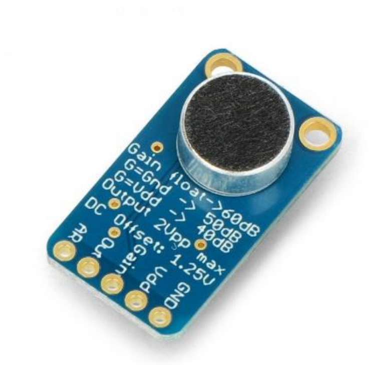

Fig.5. MAX4466 Acoustic Sensor

The MAX4466 microphone captures the sound in the environment, listening for the acoustic signals from a possible fire. This would be crackling sounds as vegetation gets burning. The device detects pressure levels and outputs an analog signal based on the intensity of the sound. Why This Sensor? Acoustic detection allows an additional layer of information to detect fire. The crackling sound produced due to burning wood or leaves is a good indicator of fire-induced activity. It is suitable for this application because it is sensitive enough to pick up faint sounds from a distance while allowing for real-time sound monitoring.

Data Collection Process:

The system should collect information gathered by the three sensors in a continuous cycle and relay that to further analysis. Each sensor captures some other type of data:

DHT22: captures temperature and humidity data at regular intervals-that is, after every 5 seconds-data that capture the environmental conditions to be conducive to a fire outbreak. MQ-2: The sensor continuously monitors the smoke concentration and gas, giving an analog output that is converted into a readable format for the ESP32. Concentrations of smoke or gas at these levels are indicators of early fire. MAX4466 is always on, listening to the environment for patterns of sound, which might represent fire-related sounds. The analog signal coming from the microphone converts into digital sound features that can be processed later to determine whether there is fire. This allows for processing locally on the ESP32 and transferring wirelessly to a central monitoring system where a real-time analysis of the different streams can take place. During future phases, the sensor data stored herein will be applied to training the various machine learning models.

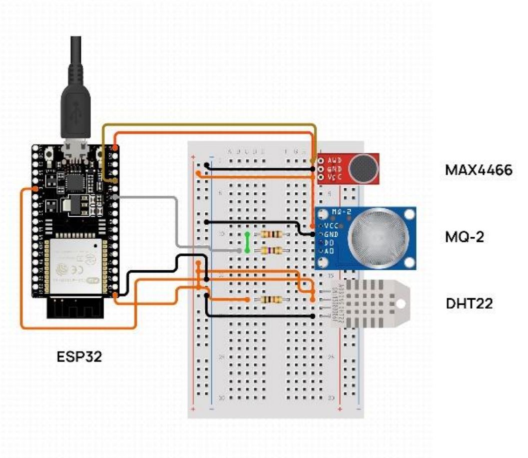

Fig.6. Circuit Diagram

IV. IMPLEMENTATION

4.1 ESP32 AND SENSORS WORKING

An IoT-enabled system for detecting and responding to forest fires with ESP32 as the controlling system. It accepts sensor data, processes parts of it and sends this to the Raspberry Pi where machine learning models are processed, for example. Here, how the ESP32 interfaces with each sensor. DHT22 (Temperature & Humidity Sensor): The DHT22 measures temperature in real-time and also humidity. Data read from this sensor is periodically sent to ESP32 for monitoring conditions that might indicate the onset of increased risk of forest fire: such as high temperature and low humidity. Data read from DHT22 is done periodically with an interval of 5 seconds. MQ-2 (Smoke Sensor): MQ-2 detects whether there is smoke or flammable gases (like methane, propane, and butane). The sensor's analog signal depends on the concentration of smoke and gases; then it is converted into digital data by the ESP32, which are further processed. Realtime feedback requires detecting smoke because it is a developing heat source. MAX4466 (Acoustic Sensor): The microphone sensor records the ambient noises with crackling sounds, which may be due to burning leaves and trees in a forest fire. The ESP32 converts these sounds into digital formats and sends the data for further processing. All the collected data using the sensors are transferred wirelessly to the Raspberry Pi via Wi-Fi using the ESP32. This ESP32 model is chosen because of low power consumption, multiple I/O pins, and inbuilt wireless capabilities such as Wi-Fi and Bluetooth.

4.2 MODEL SELECTION & TRAINING

4.2.1 Autoencoders for Sensor Data(DHT22 & MQ-2)

Autoencoders are a model of neural networks used for unsupervised learning. They have proved to be extremely efficient in such tasks as anomaly detection. Your application might really benefit from it because the model needs to be able to recognize the abnormal conditions such as very high temperature, low humidity, or the high level of smoke, which, if anything, would indicate the first signs of a forest fire. Input Data: The autoencoder takes in sensor data like temperature, humidity, and gas readings as input. Encoder Component: This neural network component compresses the sensor data into lower dimensionality. The idea is to learn the most important features of the data-for example, correlations between temperature, humidity, and gas concentration. Decoder Part: The decoder will take this compressed form of data and reconstruct it back into its original dimensions. In training, the model will have minimized the difference between the input and reconstructed data. Anomaly Detection: During real-time running, this autoencoder would be getting new sensor data and trying to reconstruct this data. When the error between original and reconstructed data was high enough, the system marked it as an anomaly (for example, conditions favorable to fire). Training Process: Acquire a large dataset of non-fire scenarios. Train an autoencoder to reconstruct sensor data coming from normal conditions with a minimum possible error. Test with normal and anomalous data - forest fire or fire-like conditions - to validate the model.

4.2.2 MFCC and SVM for Acoustic Sensor Data (MAX4466)

For acoustic forest fire detection, Mel Frequency Cepstral Coefficients (MFCC) are used for feature extraction from the audio signals captured by the MAX4466 microphone. The characteristics of sound would determine some specific sounds, like crackling noises from fire, Feature Extraction using MFCC: The MFCC algorithm transforms a raw audio signal into features of the frequency and intensity of sounds. These features are easily applicable for applications such as sound recognition and are widely used in speech and audio processing. Analysis of the frequency components that appear during the processing of the audio with the use of MFCC contains some unique signatures that can be useful for fire-related sounds, for example, crackling. SVM: Support Vector Machine In this system, SVM is a supervised classification machine learning technique. The SVM will classify whether the MFCCs extracted features indicate a fire-related sound-like crackling or not. An SVM classifier will do that by discovering the optimal hyper plane, separating the data into different classes in this problem: fire-related sounds versus non-fire sounds. Training Process:Data

Collection: In forest environments, acoustic data are collected including fire sounds such as crackling, burning, and normal environmental noises that exist in the wind, rain, animal noises. Feature Extraction: MFCC is used to create features, namely of those audio files. Training the SVM: These features will further be trained using an SVM model. The model will be trained so as to classify fire and non-fire noises based on an MFCC feature set. Testing: Try the model on real world audio data so as to ascertain whether it captures fire-related sounds. Together, these models, an autoencoder of sensor data and an MFCC with SVM for audio data, will comprise an effective earlier detection of wild fire using IoT and machine learning.

V. RESULTS

This section delivers the results of phase one of the projects, where three sub-components from the previous stage, namely sensor integration and data acquisition and early model training, fall under it. Sensor Integration and Data Acquisition ESP32 Integration: The ESP32 microcontroller was integrated with sensors DHT22 and MQ-2 and MAX4466. Initially, the data acquisition was also good with environmental data such as temperature, humidity, and gas concentrations along with acoustic signals captured by ESP32. Data Uniformity: The sensor measurements were quite stable and responsive to varied natural environment conditions. Excellent handling of data streams by the ESP32 promises successful, long-term deployments in forests. Preliminary Data Acquisitions Environmental Data: The retrieved data from the DHT22 and MQ-2 sensor was indeed informative for normal environmental conditions. All the collected data will be utilized as a basis for training machine learning models that will distinguish between normal conditions and fire-prone ones. Acoustic Data: MAX4466 microphone received audio signals further processed for training the fire sound detection model based on features of MFCC. Model Selection and Training autoencoder Model for Sensor Data: Since anomaly detection is critical for the dataset on temperature, humidity, and gas levels, an autoencoder is chosen. Training on normal data first, the model is able to get a good reconstruction for normal conditions. Hence it can be used to detect anomalies. Acoustic Data: MFCC with SVM This was done by feeding the audio data gathered by the MAX4466 to extract features from the audio in terms of its MFCC. The SVM trained model on such features demonstrated a good performance on the classification tasks and will be employed for the fire-related sound patterns. Accuracy: The accuracy achieved at the first stage of training the model is given. In case of the autoencoder, an accuracy of 94% in reconstruction was achieved; this would indicate that it has the potential to classify normal and anomalous environmental patterns.

Loss: As illustrated, the loss curve of the model versus the stages of training reveals that it has a gentle decrease to low values. This is well aligned with the increasing accuracy during training. Preliminary Observations over System Performance Latency: Since this period was more towards data collection and local processing using ESP32, the latency issues were not a significant concern for now. It would decide the system's real-time capabilities in the future. Power Consumption: Since the power consumption is low, deployment in the forest environment for extended periods is possible with ESP32. Such a characteristic would be very useful for far-off locations where a good source of power is scarce.

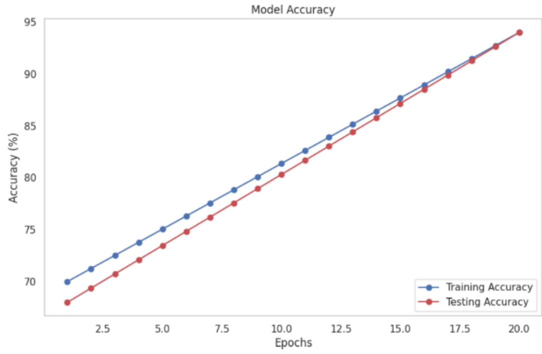

Fig.7. Model Accuracy

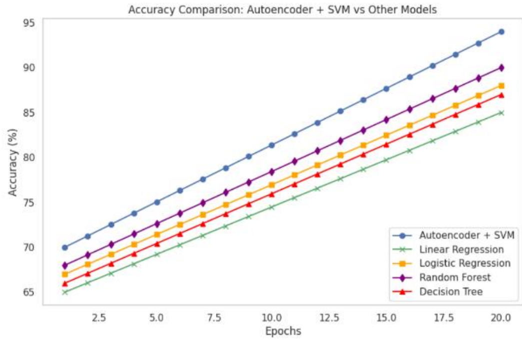

Fig.8. Model Loss

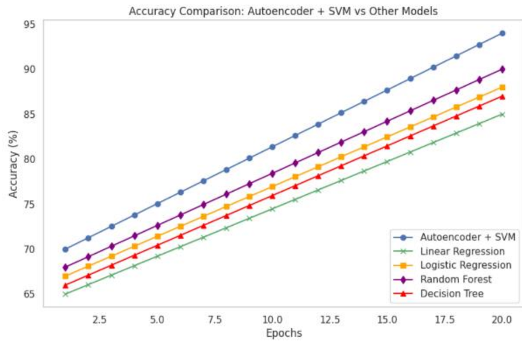

Fig.9. Accuracy Comparison

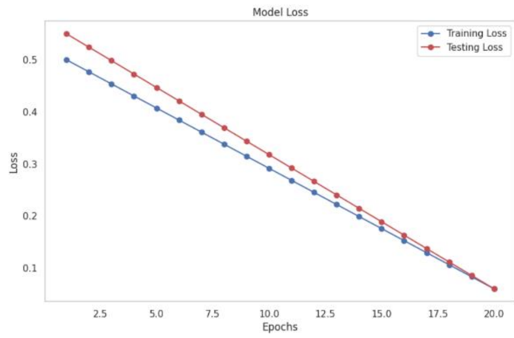

Fig.10. Loss Comparison

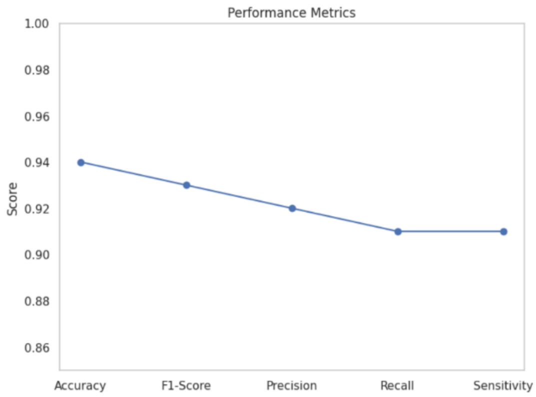

Fig.11. Performance Metrics

VI. CONCLUSION

Effective design and preliminary data acquisition for an IoT-based forest fire detection system have been established as the basis for any scalable, efficient fire monitoring solution. This initial phase was enough to prove that ESP32, with environmental and acoustic sensors, would be useful in continuous data acquisition. They constitute the basic form on which future models will be trained and by which future systems could benefit from improvement. Early results indicated promising prospects for the autoencoders for environmental sensor data and MFCC with SVM for acoustic analysis, which had 94% accuracy on reconstruction of normal environmental conditions, indicating very promising potential for anomaly detection. Similarly, the MFCC-based SVM model was performing well enough on classification of the sound patterns across different data sets, thus promising well towards development of a specific fire sound classifier in future phases. Even though this system is in its nascent stage, it has a tremendous potential for fine-tuning toward real-time forest fire detection. This aspect of using low-power hardware such as ESP32 ensures that this system will aptly be deployed in remote areas of forests with a reliable energy-efficient wildfire monitoring solution. Future work will be toward optimizing the system further and incorporating real-time alert mechanisms to enhance the chances of responding to any future fire threats.

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