A Computer Vision approach for Real-time detection of Wildfire and Humans amidst it

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***Abstract*—Given the current trend in climate change and rise in temperatures both a cause and an effect leading to a lot of catastrophes in different forms one of which is wildfires, occurring with increased frequency and intensity, devouring everything in its path. It is strenuous and challenging for rescuers to navigate through the fires and save lives stuck amidst, risking their lives as well. This phenomenon requires early actions and detection to mitigate and prevent significant losses. This paper proposes an early fire detection framework encompassing spectral, temporal and spatial feature extraction to effectively detect the presence of fires and the hotspots, synergising with a computer vision algorithm, based on yolov8 architecture, performing object detection from the input images via the drone camera for the presence of fire, smoke and humans in the affected areas.**

***Index Terms*—Wildfire detection, YOLOv8, EfficientNetV2B0, Spectral, Temporal and Spatial Feature Extraction, Comparative Analysis**

I. Introduction

Recent episodes of unusually high temperatures and long-lasting droughts due to climate change have resulted in highly favorable conditions for wildfires. The unpredictable and fast spreading of wildfires means ground-level methods of monitoring will not only be inefficient but dangerous. These methods not only risk responders' lives, but also have significant limitations, such as delayed detection, and limited coverage which means that some wildfires may not be detected at all. As a result, UAV-based wildfire monitoring has emerged as a viable alternative, offering real-time aerial surveillance and situational awareness.In this paper, we propose a more advanced wildfire detection framework by integrating UAV-based imaging, environmental sensing, and acoustic analysis to improve early detection and response. The system leverages spectral, temporal, and spatial feature extraction from images captured by drones which are fused and processed by a deep learning object detection model. Several architectures will be used to detect fire, smoke, and humans in fire-impacted areas including using YOLOv8 and EfficientNetV2B0, Voice detection and transcription, allowing quicker identification of the location of fire and modification of emergency response efforts.

Beyond UAV-based imaging, the framework incorporates environmental and acoustic data for improved detection accuracy. A ESP8266 microcontroller together with the MQ-135 sensor continuously monitors air quality, transmitting real-time data through ThingSpeak to detect fire-related anomalies. Additionally, an audio processing module captures and denoises sound signals from a microphone to identify human presence. Speech recognition techniques are applied to transcribe detected voices, and both sensor readings and transcriptions are automatically relayed via email notifications to alert emergency responders.

By integrating multiple sensing modalities, this approach enhances the precision and efficiency of wildfire monitoring. The fusion of UAV-based vision, environmental sensing, and acoustic analysis strengthens early warning capabilities, aids in search and rescue efforts, and ultimately minimizes wildfire-related casualties and damage.

II. LITERATURE REVIEW

This research paper [1] examines the integration of AI and drone -based monitoring to detect and respond to fires. AI-operated drones provide surveillance of real-time, fire detection and prevention with efficient resource management. This article indicates the contribution from intensive teaching algorithms to automatic fire detection and reduction of human intervention. This article also touches on the XAI application to increase the transparency of the decision. The study emphasizes the role of real -time data, remote measurement and pattern analysis in the prevention of forest fire. It also explains deficiencies when using AI-operated drone solutions, including hardware barriers and networking problems. Studies indicate that drone with improved AI increases early detection of fires, and they reduce the effect and reaction time. Some future applications use satellite images and IoT sensors to increase accuracy.

This study [2] explores the usage of UAVs in seek and rescue missions in wildfires. It analyzes the blessings and obstacles of drones, such as their potential to locate survivors and traverse risky terrain. The research points out case studies wherein UAVs successfully supported rescue efforts by means of collecting aerial intelligence. The research compares numerous drones, which includes fixed-wing and quadcopters, and their applicability to catastrophe reaction. It additionally explains how drones with infrared sensors and GPS can enhance rescue effectiveness. The studies outlines fundamental demanding situations together with battery existence, climate situations, and regulatory problems. Field exams indicate that UAVs can enhance situational consciousness and decrease the risk for human responders. The authors spotlight the importance of AI-based totally automation in UAV course making plans to maximise search operations. Future tasks contain incorporating device mastering models to aid self sustaining selection-making.

This article [17] checks the use of machine learning algorithms for fire preaching and detection. Research presents the use of conventions to treat satellites and drone data using practical neural networks and recurrent nervous networks (RNN). The study suggests how deep models can identify indications before fire, including heat anomalies and smoke behavior, with great accuracy. Writers comment on the value of the training model on weird data to increase the strength of the field uses. In addition, the article touches on the calculation problems that will be distributed to a machine learning model to sore units such as drones. Conclusions suggest that the AI-based methods significantly reduce false alarms and improve the first identity capacity of the fire. Future work includes learning reinforcement to maximize the fire suppression mechanism.

The authors [4] examine the functionality of the Internet of Things (IoT) and sensor -based systems, which is to detect fire in increasing the fire to Wildland. The paper checks how IoT networks with temperature, humidity and smoke sensors can trigger real-time alarms. The author shows the convergence of Lorwan and 6lowpan networks to forward data to distance a forest environment. The article highlights the role of AI-supported data analysis to detect fire spread patterns. One of the biggest challenges that feels is power consumption from sensor, which has consequences for the distribution of a wide network. Research suggests that energy -related techniques, such as a combination of solar -driven sensors, can be used to increase the life of the network. AI models are one of future applications to make smart decisions in fire control.

In this research [15] the authors have examined thermal imaging and infrared the effect of the sensor when it comes to detecting fires. The study suggests that infrared cameras on drones and satellites can capture the heat signature and detect the outbreak of possible fire before it occurs. Research identifies the benefits of using thermal sensors on optical cameras that they are able to work effectively in case of smoke or poor visibility at night. The work compares different algorithms to detect the fire that scans the thermal pattern and assigns the fire intensity classes. This task also discusses AI to combine with infrared technology to increase the accuracy of initial fire detection. Some major challenges are false alarms from heat sources other than sensors, data transmission delays and fire. Future research will quickly and more accurate fire alarm generations will improve the AI-based thermal anomaly detection model.

This paper [6] explores how satellite imagery mixed with machine gaining knowledge of models can offer better wildfire tracking and forecasting. The research targets using faraway sensing statistics from NASA's MODIS and VIIRS satellites to monitor fire hotspots. The authors offer insight into how system studying methods, including convolutional neural networks (CNNs), enhance the accuracy of satellite tv for pc-based totally detection of fires. The study emphasizes the importance of incorporating meteorological records, as an example, wind speed and humidity, to forecast fire spread. The research in addition analyzes the drawbacks of satellite-based totally structures, as an instance, interference from cloud cowl and delays in time. The findings indicate that satellite statistics mixed with drone tracking improves the tracking of fires. The future scope entails the utility of hyperspectral imaging for higher accuracy in fire type.

This research [7] discusses how AI models estimate the movement of fire. The article explains how Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models process historical fire data to predict fire movement. The research emphasizes the importance of Geographic Information Systems (GIS) in plotting fire-exposed areas and acknowledges the impact of terrain on fire spread. The study compares different forecasting models, including cellular automata and agent-based models, based on their efficiency and accuracy. It highlights the influence of real-time weather data, fuel conditions, and wind patterns on fire behavior. The authors also point out challenges with model training due to the lack of high-quality datasets. Future directions involve enhancing fire spread simulation by integrating drone and satellite data with AI-based forecasting systems.

This research paper [8] assesses the deployment of UAVs in catastrophe alleviation beyond wildfire detection. The examine emphasizes the role of drones in publish-fire surveys, damage assessments, and recovering habitats. The research investigates numerous UAV models, which include multirotors and fixed-wing cars, for aerial mapping of catastrophe regions. AI-driven picture reputation technology allow the type of burned regions and estimates of plants loss. The examine points out challenges like drone battery life, verbal exchange breakdowns, and felony boundaries on drone flight. The look at reveals that AI-primarily based automation in UAV operations can make catastrophe response more green. Future studies will cognizance on incorporating blockchain era for stable transmission of drone information in emergency conditions.

This paper [9] is concerned with deep learning methods for actual-time smoke and fireplace detection in video streams. The work assesses the overall performance of convolutional neural networks (CNNs) in identifying smoke styles from different environmental situations. The paper compares numerous deep studying fashions, inclusive of ResNet and VGG, in terms of accuracy in detecting fires. The authors emphasize the contribution of switch mastering to improving version overall performance with restrained training facts. The paper speaks approximately the relevance of processing on the brink devices which includes drones for actual-time fireplace alarms. The results show that AI-powered video analysis performs better than traditional rule-based totally fire detection. Future studies consists of developing lightweight AI fashions tailor-made for deployment on confined devices.

This paper [10] discusses the function of LiDAR (Light Detection and Ranging) era in wildfire risk assessment and wooded area planning. The studies analyzes the function of 3-D woodland models derived from LiDAR in mapping wooded area density and regions susceptible to fires. The authors evaluate using LiDAR with different aerial imagery for recording nice-scale terrain functions. The observe showcases the potential of AI-processed LiDAR information to discover tree species and gas load sample. Challenges faced include excessive expenses of LiDAR sensors and enormous computational resources required. The research means that coupled LiDAR and system getting to know improves fire hazard prediction. Development within the destiny is aimed at enhancing real-time LiDAR facts analysis for dynamic mapping of hearth hazard.

This research paper [11] investigates the utility of wireless sensor networks (WSNs) in actual-time detection of wildfires. The observe elaborates on how temperature, humidity, and gasoline sensors mounted on sensor nodes can provide early caution of fireplace. The studies compares diverse communique protocols, such as Zigbee and LoRa, for green transmission of sensor statistics in remoted wooded area regions. The authors emphasize the application of AI-based data analytics to cast off fake alarms and improve detection accuracy. Core demanding situations are network scalability, node failure of sensors, and energy consumption. The outcomes imply that hybrid sensor networks integrating WSNs with surveillance thru UAV enhance fireplace tracking. Future work entails incorporating AI-based anomaly detection fashions to maximise sensor deployment techniques.

This paper [12]makes a speciality of the abilities of self sufficient swarms of drones for detecting and suppressing fires. The research considers how coordination algorithms primarily based on synthetic intelligence allow organizations of drones to paintings collectively in actual-time at the same time as mission firefighting operations. The research considers various swarm intelligence strategies, such as particle swarm optimization and reinforcement learning, for maximizing drone movement. The paper considers drone-borne water dispensers and fire retardant drop techniques. Challenges are conversation latency, energy boundaries, and complexity of actual-time selection-making. The findings advise that AI-based totally swarm drones can greatly improve firefighting operations. Future paintings is directed toward combining cloud-primarily based AI for global coordination of firefighting drones.

This research paper [13] analyses the evolution of AI-pushed early caution systems for wildfire prevention. The look at explains how machine gaining knowledge of algorithms take a look at past fireplace records, weather patterns, and satellite photos to forecast hearth threat. The authors look at the convergence of cloud computing with edge AI for actual-time wildfire detection. The research emphasizes the want for interdisciplinary collaboration in building robust wildfire early caution frameworks. The important challenges are statistics privacy issues, model interpretability, and the requirement of huge education datasets. The results suggest that AI-based totally early caution structures beautify emergency reaction times and disaster preparedness. Future studies guidelines consist of making use of federated mastering to enhance prediction models while keeping statistics security.

This paper [14] highlights how unmanned aerial cars (UAVs) have become increasingly treasured equipment for detecting, tracking, and coping with wildfires. It gives a detailed have a look at current UAV-based systems, masking the entirety from onboard sensors and hearth detection technologies to coordination techniques and emerging collaborations with floor vehicles (UGVs). The authors emphasize the advantages of UAVs, together with their flexibility, capability to access remote regions, and relatively low operational costs—making them particularly beneficial for tracking huge or hard-to-attain hearth zones. Although latest development in AI and laptop vision has greater hearth detection skills, the paper also factors out key demanding situations, which includes restricted strength supply, inadequate datasets, and the want for greater actual-global validation. Ultimately, the authors call for the development of clever, integrated structures which could autonomously gather facts, make selections, and work collaboratively to respond greater effectively to wildfires.

This article [15] sees how drone forests can play an important role in monitoring wildlife during fire, and emphasizes their increasing value in environmental monitoring. Writers explain how UAVs equipped with high-resolution and thermal cameras can track animal movement and also detect the outbreak of fire in difficult to wheels or remote areas. Compared to traditional methods that depend on grassroots layers, drones provide quick response, extensive coverage and more accurate information. That being said, the paper also exposes certain limits, such as low performance in excessive heat and poor visibility during active fire. In order to remove these challenges, the author suggests developing special software and intelligent algorithms that can increase the monitoring of wildlife-special during large moments such as withdrawal, after-fi assessment and habitat extraction.

III. METHODOLOGY

IMAGE PROCESSING

A. Dataset Preprocessing and Augmentation

Post collection of dataset, 24,003 images at training set, 1017 images at validation set and 731 images at test set. Auto-orienting and resizing of images through stretching to 640×640 were done as part of the preprocessing steps. Data augmentation was used to improve the model, producing three output variations from each training example. Flip horizontally and vertically, 90° rotations (clockwise, counterclockwise, and upside-down), random rotation within -15° to +15°, and shearing horizontally and vertically of ±10°.

B. Feature Extraction

1) Spatial Information: The spatial evaluation begins by computing the grayscale version of the input image. Smoothing filters are then applied to estimate the background by averaging the surrounding pixel values. These average pixel values are used to calculate the background intensity. Spatial information is determined by subtracting the grayscale image from its background estimation. The resulting difference output is used to assess both texture and intensity variations.

$$S_t(x,y) = I_{gray}(x,y) - \frac{1}{N_b}\sum I_{gray}(i,j) \tag{1}$$

where N_b represents the number of neighboring pixels used for background estimation, and $I_{gray}(x,y)$ denotes the grayscale intensity at a given pixel location.

2) Temporal Information: Temporal characteristics record pixel intensity variations over time. The contrast between the grayscale intensity of the current image and the previous frame is calculated to identify motion changes, which are essential for detecting dynamic objects such as fire and smoke:

$$T_t(x,y) = I^t_{gray}(x,y) - I^{t-1}_{gray}(x,y) \tag{2}$$

where $I^t_{gray}(x,y)$ and $I^{t-1}_{gray}(x,y)$ represent the grayscale intensity at the current and previous time steps, respectively. If there is no previous frame available, the temporal information is set to zero.

3) Spectral Information: The spectral feature extraction method uses intensity tests between color channels to find fire signals effectively, reducing background artifacts using red indications for fire detection. Improved fire detection reliability occurs when the system compares red to blue channels to identify fire areas while removing environmental disturbances.

$$Sp_t(x,y) = I_{red}(x,y) - I_{blue}(x,y) \tag{3}$$

where $I_{red}(x,y)$ and $I_{blue}(x,y)$ are the pixel intensity values in the red and blue channels, respectively. This difference enhances fire-related features while minimizing background noise.

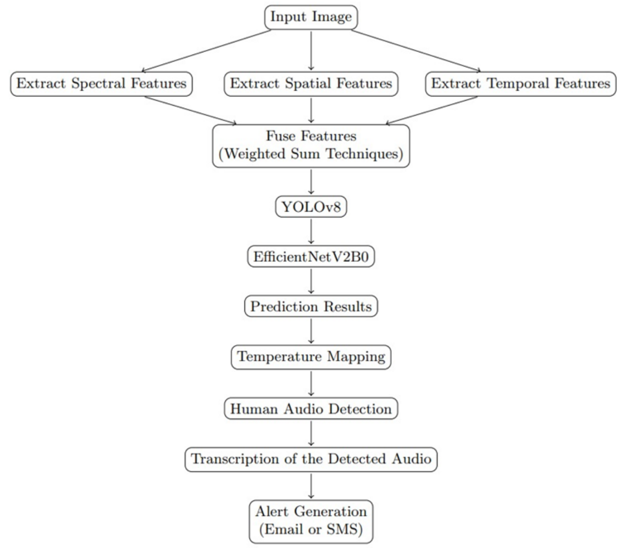

Fig. 1. Model Architecture

4) Feature Fusion and Analysis: The extracted spatial, temporal and spectral features are combined via the weighted technique to optimize the representation of the characteristics. The fused feature map is computed as follows:

$$F_t(x,y) = w_s S_t(x,y) + w_t T_t(x,y) + w_{sp} Sp_t(x,y) \tag{4}$$

where w_s, w_t, and w_{sp} are the weight factors assigned based on the importance of each of the different features. This fusion helps improve the accuracy of fire, smoke, and humans, making human wildfire monitoring systems more robust.

C. Yolov8 and EfficientNetV2B0

YOLOv8 was used for object detection using the yolov8s.pt pre-trained weights. The data configuration file (data.yaml) was used to specify the essential training parameters. Over 100 epochs were used for training the model using the image resolution of 640x640 and batch size of 16 to boost the accuracy and the performance of detection.

The way YOLO operates is by splitting the RGB input image into an S × S grid, with each and every cell in the grid predicting objects whose center lies within it. Each cell predicts the bounding boxes that contain the coordinates (x, y, w, h) and a confidence, which represents both the probability of the object's presence and the locality of its accuracy. To maintain consistency between bounding boxes and image dimensions, normalization techniques were applied. The (x, y) coordinates indicate the center of the bounding box relative to the corresponding grid cell. The YOLOv8 model architecture includes several convolutional layers, batch normalization, and residual connections, which enable efficient feature extraction. The backbone, mimicking CSPDarknet, is designed to extract high-level features of an image, and subsequent layers enhance object detection. The last layer of the model predicts bounding box coordinates as well as class probabilities.

The network architecture is integrated with convolutional layers and pooling layers and dense layers for pretraining. Extra accuracy gains were obtained by including more convolutional and fully connected layers. The 640×640 resolution was set in order to aid in fine-grained visual detection.

To reduce localization error and enhance average precision, YOLOv8 loss function includes classification loss, localization loss, and confidence loss. Localization loss measures specifically the bounding box prediction error, only looking at the box accountable for detecting the object. The model makes the detection more reliable by optimizing confidence and localization loss parameters.

In order to further improve, EfficientNetV2B0, a deep neural model, extracts spatial features, encoding high-level structural information.Additionally, greyscale images were subjected to the Fast Fourier Transform (FFT) in order to compute spectral characteristics, which produced frequency-domain representations of identified items.

D. Temperature Mapping

The system reads an input image by loading it in RGB format through OpenCV. The RGB image is then mapped into a grayscale representation, which allows pixel intensity mapping to a specified range of temperatures.To have uniformly distributed intensity values, the grayscale image is normalized between [0,1] range through Min-Max normalization. The Normalized intensity values are linearly transformed to a temperature scale, that ranges from 0°C to 100°C according to the following transformation:

$$T(x, y) = I_{\text{norm}}(x, y) \times (T_{\max} - T_{\min}) + T_{\min} \tag{5}$$

where $T(x, y)$ represents the temperature at a given pixel, $I_{\text{norm}}(x, y)$ is the normalized grayscale intensity, and $T_{\max}$ and $T_{\min}$ are the predefined temperature limits.

The normalization is performed using the Min-Max scaling method:

$$I_{\text{norm}}(x, y) = \frac{I(x, y) - I_{\min}}{I_{\max} - I_{\min}} \tag{6}$$

where $I(x, y)$ is the grayscale intensity at pixel (x, y), and $I_{\min}$ and $I_{\max}$ are the minimum and maximum intensity values in the image, respectively.

The temperature map is visualized with the Inferno colormap, which appropriately highlights intensity variations. A color bar is provided to display temperature values, rendering an interpretable heatmap of the input image.

SOUND PROCESSING

E. Automated Human voice detection,Speech-to-Text Transcription and Email Notification System

The proposed system, accessible through a web-based interface, human voice recognition, facilitates automatic speech-to-text transcription, email extraction, and email notifications. An audio file is processed via a Flask-based API, where it undergoes standardization and analysis for further processing. The file uploaded is saved in a predefined folder, and the Librosa library is utilized to read the audio at a standardized sampling rate of 16 kHz for compatibility with the Whisper model. For better quality of transcription, noise reduction is used with the noisereduce library in order to suppress background noise but leave speech content unchanged. The minimum test is done to identify whether the given audio contains human speech or not. This is accomplished through energy-based voice activity detection, for which the system sums the amplitudes of the squared values of the audio signal. If the value of the energy is above an already set limit (0.01), human speech presence is confirmed and transcription begins.

When human speech is identified, the Whisper model is utilized for automated transcription. The model analyzes the audio input and produces text output with high accuracy. The process of transcription is optimized by utilizing the base Whisper model, which achieves a balance between computational efficiency and accuracy. To make it more usable, the system also has an automated email notification system. An email with the transcribed text is sent to a specified recipient if the transcribed speech has more than three words. This feature is coded using the smtplib library, which creates a secure SMTP connection to send emails. The whole process is encapsulated in a Flask-based REST API where users can upload audio files obtained from the presence of microphones on drones if any and get transcriptions in real time. The API gives back a JSON-formatted response with the human voice detection status, transcribed text, and extracted email addresses if any.

This step enables covering all aspects, not only processing Visual data,alongside Image, Sound is processed and further in the next steps, Sensor Integration provides with the Air Quality details.

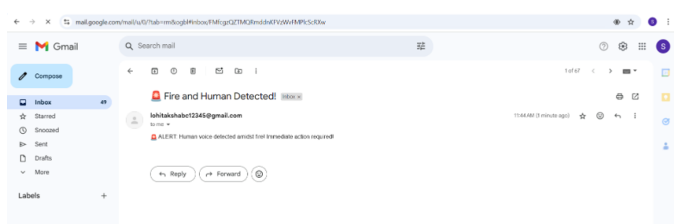

Fig. 2. Mail alert post Human Voice detection.

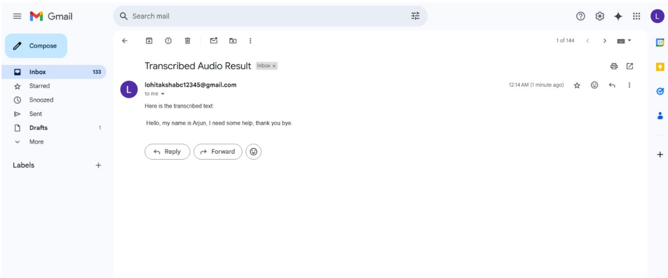

Fig. 3. Transcribed Audio Result via Email.

SENSOR INTEGRATION

F. IoT-Based Air Quality Monitoring and Alert System Using ESP8266

The design uses an ESP8266 microcontroller and MQ-135 gas sensor to measure the quality of surrounding air in real time.The system is Wi-Fi enabled, which facilitates proper communication between the ESP8266 module and external cloud services. The ESP8266 Web Server provides local accessibility, and hence users can fetch real-time sensor data using HTTP requests. The hardware components used are:

ESP8266: Processing and communication microcontroller. MQ-135 Sensor:Detects gases including CO_2, NH_3, NO_2, and alcohol vapours to determine the quality of the air. Wi-Fi Communication: Used for IoT communication for data exchange.

The MQ-135 gas sensor provides analog readings proportional to the concentration of gases in the environment. The acquired sensor value is converted into voltage using the following equation:

$$V = \frac{\text{Sensor Value} \times 3.3}{1023} \tag{7}$$

where V represents the measured voltage, and 3.3V is the reference voltage of the ESP8266 microcontroller. The analog output of the MQ-135 sensor is read using the ADC (Analog-to-Digital Converter) of the ESP8266, ensuring accurate signal acquisition.

To ensure continuous monitoring, sensor data is updated every 15 seconds. The ESP8266 reads the air quality values and processes them for further transmission to cloud-based services. The sensor readings are analyzed to detect fluctuations in air quality, triggering alerts when pollution levels exceed a predefined threshold.

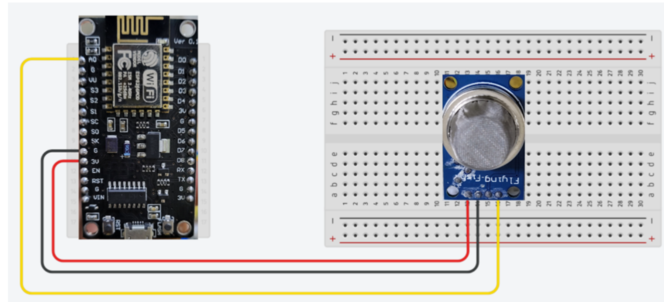

Fig. 6. Circuit Diagram

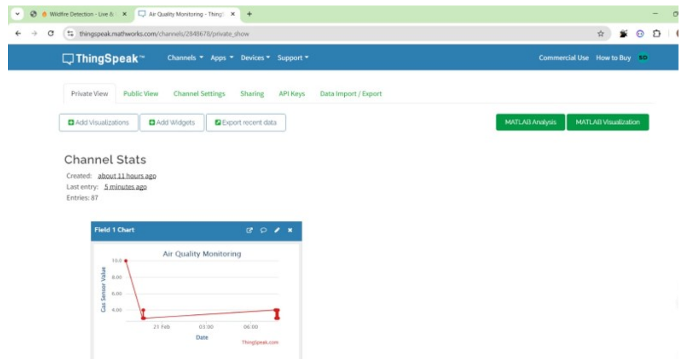

Fig. 4. Air Quality Monitoring with Thingspeak dashboard

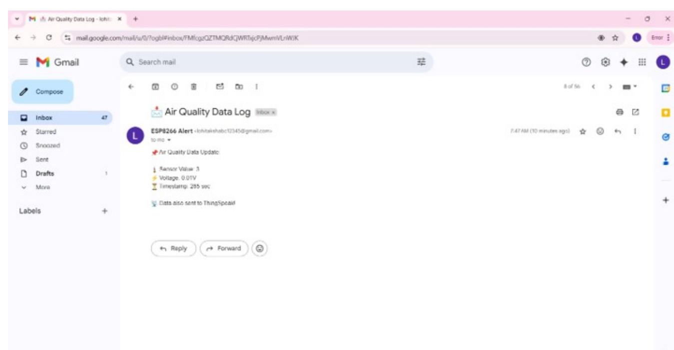

Fig. 5. Air Quality Data Log via Email Alert

The collected data is then transmitted to to ThingSpeak, an IoT cloud-based analysis platform for visualization and further processing, and to enable real-time access and visualization.The ESP8266 performs an HTTP-based API request for updating the cloud database.An automated e-mail warning system is implemented with the help of the ESP Mail Client Library. Once the air quality drops below a predefined level, a warning e-mail is generated using SMTP (Simple Mail Transfer Protocol). The e-mail contains: Sensor measurements (air quality index and voltage). Alert time stamp. Warning message for poor air quality. The email sending process uses the SMTP authentication protocol in order to communicate securely.

IV. Results and Discussion

A. Comparative Analysis of Feature Extraction Techniques

To compare the efficiency of the feature extraction methods used with spectral, temporal, and spatial features and the EfficientNetV2B0 model,a baseline model was used without these sophisticated feature extraction methods. The results from both models were compared to identify the improvements gained with the inclusion of feature extraction methods. The baseline model utilized only object detection with YOLOv8 without additional feature extraction layers. The enhanced model employed spatial feature extraction via EfficientNetV2B0, spectral analysis via Fast Fourier Transform (FFT), and temporal characteristics of sequential frame handling. The feature fusion mechanism also synthesized these extracted features via a weighted combination method:

$$F_{\text{fused}} = \alpha F_{\text{YOLO}} + \beta F_{\text{spatial}} + \gamma F_{\text{spectral}} \tag{8}$$

where F_{YOLO} represents object detection features, F_{spatial} represents extracted spatial features, and F_{spectral} denotes frequency-domain features derived from FFT.

Performance indicators like mean average precision (mAP), processing time, and detection confidence were compared between models. The results proved that the fused feature extraction model significantly improved the model's detection robustness and accuracy, particularly in occlusion and varying lighting conditions. The gains obtained, validate the use of multi-modal feature fusion to improve real-world object detection performance.

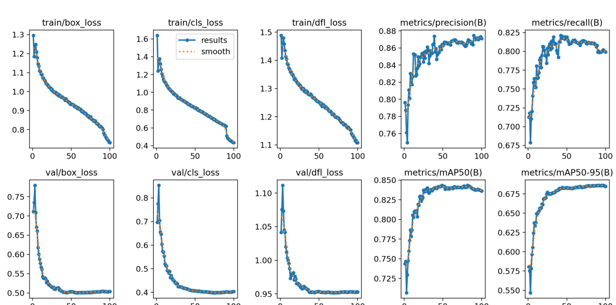

Fig. 7. Training Performance Metrics of the Enhanced Model with Feature Extraction Techniques.

TABLE I
EVALUATION METRICS

Metrics	Value
Train/Box Loss	0.73
Train/Class Loss	0.43
Train/DFL Loss	1.10
Val/Box Loss	0.50
Val/Class Loss	0.40
Val/DFL Loss	0.95
Precision	0.87
Recall	0.79
mAP50	0.83
mAP50-95	0.68

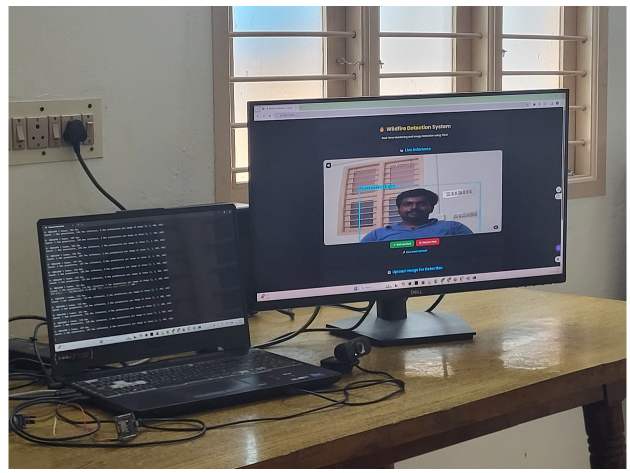

Fig. 8. Real-Time Human Detection Using a Web Camera.

The confident score for the prediction results highlights the improvement of the enhanced model with the aid of the preprocessing techniques which could also possibly assisst in early detection when a continous input of progressive frames is fed as the model would analyse the pixel change overtime in the frames when a fire starts to catch and detect the fire in its early-stages.

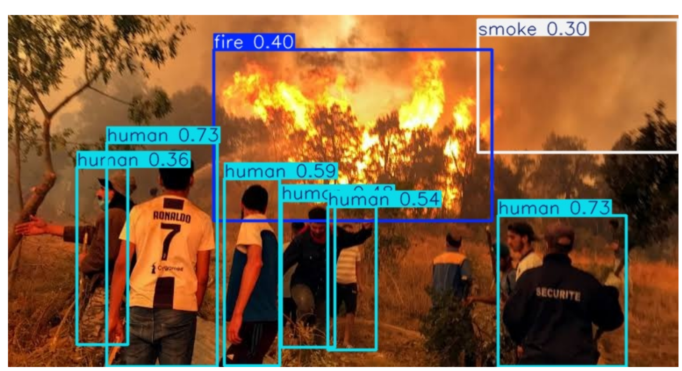

Fig. 9. Prediction Results from the Baseline Model.

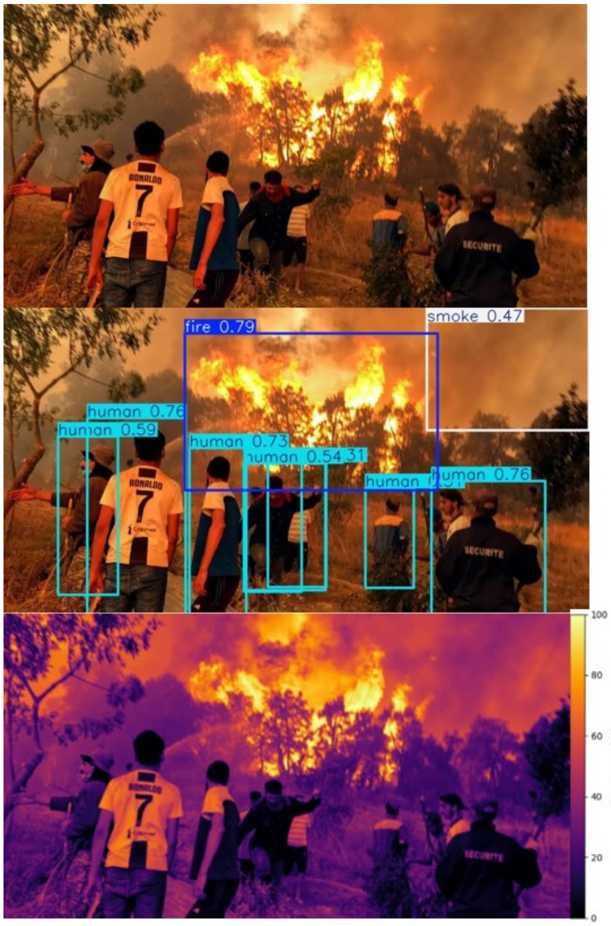

Fig. 10. Original Image, Prediction Results, Generated Temperature Map from the Enhanced Model.

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