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AI-Powered Forest Fire Detection and Early Risk Prediction System

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Abstract - Forest fires pose a critical threat to biodiversity, environmental stability, and human safety, while their incidents are gradually on the rise owing to climatic changes, land-use changes, and rising temperatures. Most conventional monitoring techniques-satellite imaging, manual patrolling, threshold-based sensor systems-suffer from delayed detection, low spatial resolution, and high false alarm rates [3,4,16,26]. More recently, because of developments in AI, ML, DL, IoT, and remote sensing, significant strides have been made in wildfire prediction, early detection, and automated response [1,2,5,6,7,9,11,17,20,23,27,30]. Motivated by such developments, this work reports an integrated AI-powered forest fire detection and early risk prediction system, integrating CNN-based visual fire detection, random forest-based environmental risk classification, and IoT-driven sensor monitoring, as proposed in the project document.

The proposed system uses a transfer-learned CNN model to identify flames and smoke in real-time through webcam feeds, similar to the works on DL in [5], [6], [17], and [23], and optimized architectures like FireXNet and GoogLeNet-based detectors in [15] and [25]. Meanwhile, a Random Forest classifier will predict fire-risk levels of low, medium, and high from temperature, humidity, and air quality data captured using DHT11 and MQ-135 sensors. This will align with ML-based prediction studies found in [4], [8], [10], [18], and [19] and environmental analytics based on multisensor systems in [12], [14], [20], and [28]. Features extracted from both models will be combined into a decision-fusion mechanism that will trigger proactive alerts through LED and buzzer hardware, enabled by NodeMCU ESP8266, conforming to IoT-based early warning systems in [1], [9], [12], and [21] and secure forest monitoring frameworks in [22]. It ensures high accuracy and speed in response time, and robustness of operations, thus supporting the efficiency of the proposed multimodal AI-IoT integration for real-time wildfire monitoring. These features address the critical gaps in existing detection technologies and fall within various current global research trends in satellite-aided detection [3, 16, 26], UAV-supported surveillance [27, 29], and crowdsourced fire reporting [13].

Key Words: Forest fire detection; Early fire prediction; Convolutional neural network; Random forest; Internet of Things; DHT11; MQ135; NodeMCU ESP8266; Machine Learning; Deep Learning; Remote sensing; Wildfire monitoring; Fire risk classification; Sensor networks; Decision fusion.

1. INTRODUCTION

Forest fires are one of the most disastrous environmental hazards around the world and cause serious ecological degeneration, economic loss, and threats to human life. Their frequency and intensity have noticeably risen due to rising global temperatures, extended droughts, deforestation, and anthropogenic activities [2], [7], [11]. Traditional methods of fire monitoring usually have high latency, low spatial resolution, interference from adverse

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weather conditions, and restricted coverage in terms of detection with human patrolling, watchtowers, thermal sensors, and satellites [3, 4, 16, 26]. For this reason, the detection of fire usually occurs after they have grown further and the mitigation process is delayed with aggravated magnitudes of damages.

Recent advancement in AI, ML, DL, IoT, and remote-sensing technologies has changed the dimensionality of detection and prediction in case of wildfires. Quite a number of related research works established the potentials of computer vision and CNN-based architectures such as YOLO, InceptionResNet, GoogLeNet, and customized versions of CNN in terms of real-time detection of fire and smoke with high accuracy using satellite images, UAV videos and video surveillance data [5], [6], [15], [17], [23], [25], [29]. Similarly, several ML algorithms such as Random Forest, SVM, kNN, Logistic Regression and Extreme Learning Machines have also reported promising performance while forecasting fire occurrence zones using meteorological, environmental and spatio-temporal data [4], [8], [10], [18], [19], [20], [28]. IoT-enabled fire monitoring systems augmented the capability for early detection by integrating temperature, humidity and gas sensors on a microcontroller-based network that continuously monitor the environmental conditions [1], [9], [12], [14], [21]. Different multi-sensor fusion techniques, long-range communication, crowdsourcing with smartphones and frameworks for secure data transmission were proposed to enhance scalability and reliability along with real-time responsiveness of the wildfire alerting system [13], [20], [22]. The use of drone-assisted detection, satellite-based situational awareness and geospatial analytics has also gained widespread popularity in order to extend the coverage and precision aspects in monitoring applications [16], [26], [27], [30]. These, along with the deficiencies of traditional systems, motivate the implementation of an AI-enabled forest fire detection and early risk prediction system, integrating CNN-based visual fire detection and Random Forest-based risk prediction with IoT-driven environmental sensing. In this framework, flame and smoke detection are done by live video analysis using a webcam. The two IoT sensors-DHT11 and MQ-135-operate in continuous monitoring of ambient temperature, humidity, and air-quality parameters with respect to fire risk assessment. A decision-fusion mechanism unifies the predictions from both models and thus triggers immediate on-site alerts through LED and buzzer units via the NodeMCU ESP8266 microcontroller. In view of the above, the main goal of this work will be the development of a low-cost, scalable, real-time multimodal framework for the detection of wildfire that contributes to enhance early warning capability and reduces the response time. Such a system will improve preparedness for wild fire with the integration of AI, ML, and IoT for sustainable disaster prevention strategies.

2. BACKGROUND AND LITERATURE REVIEW

One of the oldest challenges has been to detect and predict wildfire, where the processes of fire ignition and propagation are controlled by the complex interplay of climatic, environmental, and anthropogenic variables. Traditional systems for fire monitoring consider satellite imagery, manual reporting, thermal scanners, and meteorological indicators [3, 4, 16]. Although these techniques have produced regional-scale observations, their respective disadvantages concern low temporal frequency, interference by cloud cover, no early warning capability, and inability to recognize small or incipient fires [7, 11, 26]. These disadvantages have motivated interest in the development of an automated intelligent system able to realize real-time surveillance with rapid decision-making.

Advances in DL have significantly improved the visual detection of fire by enabling automatic feature extraction from images and sequences of video. Several pieces of research have used CNN-based architecture for flame and smoke detection in realistic environments. Works in [5], [6], and [17] explored custom CNN and transfer-learning models for fire identification using surveillance cameras and UAV images. The YOLO-based detectors demonstrated high-speed and high-precision fire detections that are of great assistance in recognition at an early stage [23], [25]. Other works, such as in [15] and [29], included lightweight CNN models optimized for embedded systems, showcasing the feasibility of deploying DL models on low-power hardware, similar to what was done in the present project. The FireXNet model discussed in [18] further underlined the effectiveness of explainable AI for transparent and interpretable wildfire detection.

Apart from the more direct approach to visual detection, ML has been widely applied for the prediction of fire hazards based on environmental and meteorological parameters. Random Forest, SVM, Logistic Regression, and Gradient Boosting models have proved efficient in predicting fire susceptibility with respect to temperature, humidity, wind speed, vegetation indices, and pollutant concentrations [4], [8], [10], [18], [19], [20]. Studies in [12] and [28] identify that multi-parameter fusion enhances the prediction reliability while explaining how the fusion of gas sensors, humidity and thermal data enhances the reliability of the prediction. These findings give direct support to the DHT11 and MQ-135 sensors applied in the implementation of the project document. IoT technologies have further enhanced the process of monitoring wildfires through distributed sensor networking, real-time communication, and automated alert mechanisms. The IoT-based frameworks in [1], [9], and [14] have been integrated with temperature, humidity, and gas sensors for continuous monitoring, while systems in [21] and [22] provide protocols for secure communication along with low-power microcontroller platforms for deployment in forests. On one hand, crowdsourced and mobile-based reporting have been presented in studies such as those in [13] and [20]; on the other hand, long-range communication technologies such as LoRaWAN have been proposed to extend the coverage over remote forest areas. Recently, remote sensing and UAV-assisted systems have gained prominence for large-scale situational awareness. Satellite-based fire detection platforms discussed in [3], [16], and [26] provide macro-level analysis using thermal anomaly detection, while UAV-based surveillance frameworks in [27], [29], and [30] provide higher spatial resolution and flexibility in the monitoring of forest interiors. Although effective, these methods have huge cost and infrastructure involvement and hence make the hybrid AI-IoT systems all the more apt for applications needing low-cost continuous monitoring. In large measure, the literature shows huge convergence of findings toward a multimodal system that integrates visual analytics, sensor data, and machine learning for high accuracy in detection, fast response time, and greater reliability. The proposed system, motivated from these findings, embodies a dual-model approach-CNN for visual detection and Random Forest for risk prediction-along with IoT-based sensing and microcontroller-driven alerting in coherence with the emerging trends and best practices across the contemporary research landscape.

3. SYSTEM ARCHITECTURE

That is, the solution provided will be based on a multi-modal architecture, using Deep Learning–based visual detection of fire, Machine Learning–based prediction of environmental risk, and IoT-driven real-time monitoring to provide both high accuracy and fast response. It should also be low-cost and scalable with respect to deployment in a forest environment where connectivity and power are scarce resources, as is widely adopted in state-of-the-art modern AI–IoT monitoring systems for wildfire detection described in [1], [9], [12], [21], and [22].

A. Overall Architecture

The architecture comprises three main subsystems:

- Visual Fire Detection Module,
- Environmental Risk Prediction Module, and
- IoT Alert and Monitoring Module.

These subsystems communicate through a central Python-based middleware that fuses data and integrates decisions in a similar way to hybrid architectures outlined in [5, 6, 17, 23, 28].

Below is a high-level block diagram of the architecture described in the project document. It would include:

- Webcam/Camera Input
- CNN DETECTION ENGINE
- Temperature-Humidity-Gas Sensor Unit
- Random Forest Prediction Engine
- NodeMCU ESP8266 Control Layer
- Warning Actuators (LED, Buzzer)
- Cloud/Local Monitoring Interface

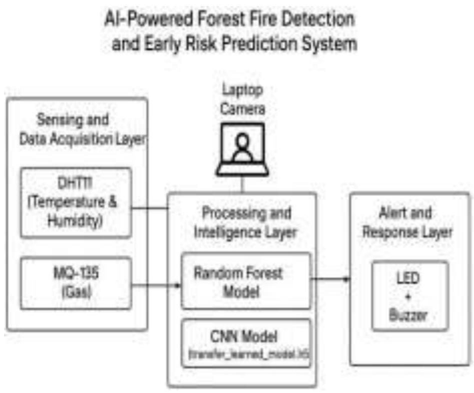

Fig1. System Architecture

B. Visual Fire Detection Module

In this context, real-time webcam frames have been processed with respect to flame and smoke pattern recognition using the transfer-learned CNN model. The architecture is adopted from CNN- and YOLO-based fire detection systems reported in [5], [6], [15], [17], [23], and [25]. The convolutional layers extract spatial information, while fully connected layers classify the scene as fire or non-fire.This model is optimized for lightweight deployment, with principles utilized in edge-oriented models such as FireXNet and MobileNet-based detectors in [18], [29].

C. Environmental Risk Prediction Module

This module uses environmental data from:

- DHT11 for temperature and humidity
- MQ135 For Air Quality and Gas Concentration

These sensor readings then feed into a Random Forest classifier trained for the prediction of fire risk levels such as Low, Medium, and High. The Random Forest classifier is robust, able to handle nonlinear data, and highly interpretable; hence, it is recommended for ML-based risk prediction approaches in state-of-the-art works such as [4], [8], [10], [18], [19], and [20].

Actually, environmental multi-parameter fusion, such as in [12], [14], and [28], enhances this risk estimation approach in ensuring reliability.

D. IoT Monitoring and Alert System

This system uses an edge controller, NodeMCU ESP8266, interfacing with sensors and alerting peripherals. The microcontroller receives the predictions from the ML model by serial/Wi-Fi communication and thus triggers :

- LED indicator for risk conditions
- Buzzer to create Immediate Alarms

Such IoT-enabled alert frameworks find broad adoption in real-time fire detection systems in [1, 9, 14, 21, and 22]. It ensures low power consumption due to Wi-Fi–based microcontrollers and supports local or cloud-based monitoring.

E. Data Fusion and Decision Integration

The outputs of both detection paths are combined by a decision-fusion mechanism: It will trigger an alert if CNN detects flames or ML predicts a high-risk condition. In the event of both modules agreeing on a threat, the system raises a critical alert for quick response. The methods for detection fusion are also recommended in the domain of wildfire research, especially those in multimodal systems reported in [20], [23], [28], and [30].

F. Communication and Scalability

This architecture is scalable to multiple sensor nodes and cameras across larger forest regions. In future extensions, we can use LoRa, GSM, satellite links, or drone-based image capture as in remote sensing systems described in [3], [16], [26], [27], [30].

4. METHODOLOGY

The methodology of the AI-powered Forest Fire Detection and Early Risk Prediction System will involve Deep Learning–based visual analysis, Machine Learning–based environmental risk classification, and IoT-enabled sensor monitoring. This is a modular and sequential workflow that ensures real-time data acquisition, prediction accuracy, and efficient alerting. The steps of the methodology conform to established techniques in contemporary research in wildfires as reported in [1], [5], [9], [17], [20], [23], and [28].

A. Data Acquisition

Acquired are two types of data:

1. Capture Visual Data

A USB/Web camera captures, in real-time, continuous video frames of the monitored environment. In fact, the same real-time visual acquisition techniques are adopted in the DL-based fire detection systems provided in [5], [6], [17], [23] and [25].

2. Environmental Sensor Data

Temperature, humidity, and air quality readings are collected with:

- DHT11 Sensor (Temperature & Humidity)
- MQ-135 Sensor: CO_2, NH_3, NOx und VOC-Konzentration

The environmental sensor-based fire monitoring is aligned with the IoT frameworks presented in [1,9,12,14,20,28].

B. Preprocessing

1. Image Preprocessing

Input video frames undergo:

- Resizing
- Normalization
- Color-space adjustments

These steps improve the performance of the model according to the CNN-based wildfire studies in [5], [17], [23] and [29].

2. Cleaning Sensor Data

Sensor readings are filtered and averaged to reduce noise and oscillations. Missing values and anomalies are corrected by the rolling average, following environmental pre-processing techniques discussed in [4], [8], [10], [18].

C. CNN-Based Visual Fire Detection

1. Model Architecture

It uses a transfer-learning CNN model that leverages pre-trained weights for better flame and smoke detection. Transfer-learning-based detection has been effective in several studies like [6], [15], [17], and [25].

2. Training and Validation

- This dataset consists of fire and no-fire images from openly available repositories, supplemented with generated samples.
- Image augmentation is employed to improve generalization.
- The training follows protocols of supervised classification similar to [5], [23], [29].

3. Real-Time Detection

- The live frames do a forward inference by the CNN trained.
- The fire/non-fire classification is determined by a threshold on the probability, consistent with the real-time detection strategies in [17], [25].

D. Random Forest-based Environmental Risk Prediction

1. Feature Extraction

Sensor features include the following:

- Temperature (°C)
- Humidity (%)
- Air Quality Index (MQ-135 output)

These parameters agree with the risk indicators according to ML-based fire prediction research [4], [10], [18], [19], [20].

2. Model Training

- Train a Random Forest classifier these to predict the risk level: Low, Medium, High.
- Random Forest is selected because it has robustness, high interpretability, and strong performance in the environmental prediction tasks [8], [10], [18], and [20].

3. Inference of Risk

- The model predicts the fire risk in real time during deployment, integrating multi-sensor inputs.
- The environmental fusing and risk estimation reflect methodologies in [12], [14], [28].

E. IoT-based Alert and Control System

1. NodeMCU ESP8266 Integration

The ML model outputs are fed into the NodeMCU ESP8266. The latter then controls:

- LED Indicator Risk Visualization
- Buzzer Alarm Warning Immediately

Such actuator-based IoT alerting frameworks have been implemented in wide fashion for fire detection systems by works in [1], [9], [14], [21], [22].

2. Serial/Wi-Fi Communication

The model's predictions will be transferred serially or via Wi-Fi, thus making it enable local and remote alerting, similar to the communication approaches of IoT in [12], [20] and [22].

5. IMPLEMENTATION

The proposed AI-powered forest fire detection and early risk prediction system will be implemented by integrating hardware, software, machine learning models, and communication interfaces. Such a system was deployed on-site as a hybrid real-time monitoring framework, which features a deep learning-based visual detection pipeline using CNNs, a Random Forest-based classifier to assess environmental risks, and an IoT-enabled alerting mechanism. The following implementation details best practices adopted in prior AI and IoT-based wildfire systems discussed in [1], [5], [9], [14], [17], [20], [22], [28].

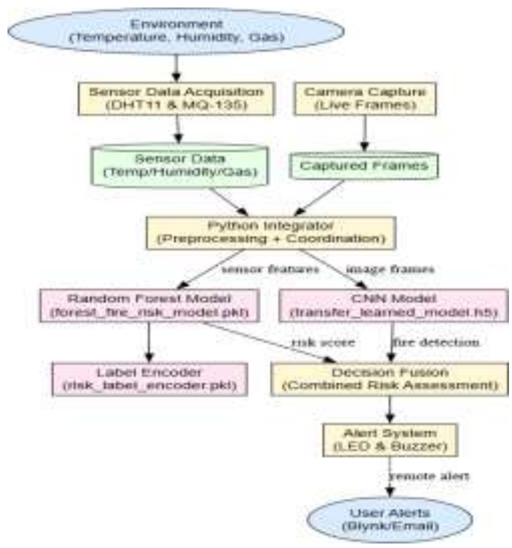

Fig2. Implementation Diagram

A. Hardware Implementation

1. Sensor Module

- DHT11 for measuring temperature and humidity

- MQ-135 for air and smoke pollutants' concentration sensing.

These sensors were selected based on their wide use in environmental monitoring systems as reported in [9], [12], [14], and [20]. Both sensors are interfaced with the NodeMCU ESP8266, a Wi-Fi enabled microcontroller known for low power consumption and fast response times as stated in [21] and [22].

2. Microcontroller Setup

NodeMCU ESP8266 collects the sensor readings, performs monitoring logic based on threshold values, and triggers actuators. The microcontroller is programmed by using an Arduino IDE, which agrees with [1] and [9] on implementing light-weight IoT-based fire alerting systems.

3. Notification Devices

The alert mechanism includes:

- LED Indicator: Provides current status of the fire hazard.
- Active buzzer: In case of a detected danger, it provides sound warnings.
- IoT wildfire frameworks in [14], [21], [22] use actuator-based alert systems.

B. Software Implementation

1. Python-Based Processing Engine

The main tasks implemented by the Python application running locally are three in total:

- Perform inference CNN on frames from webcam
- RF Prediction by using Sensors Input
- These fused outputs are then sent to the NodeMCU using Serial/Wi-Fi communication.
- Python is chosen due to its strong ML/DL ecosystem, which is consistent with the implementations in [5], [6], [17], [25].

2. Sensor Data Acquisition

The PC receives sensor values transmitted by NodeMCU. Data is parsed, cleaned, and forwarded to the ML classifier. This follows the usual IoT–PC integration workflows seen in [12], [20], [28].

C. CNN Model Implementation

1. Model Selection

It implements a transfer-learning CNN architecture to carry out real-time fire and smoke detection. Pretrained weights accelerate convergence and improve accuracy, as demonstrated in [5], [6], [15], [23], and [25].

2. Training Process

The model is trained on a dataset of images with variations in fires and non-fires, and training includes:

- Data augmentation
- Normalization
- Batch Optimization
- cross-entropy loss minimization

The methodology used for training follows deep learning practices used in wildfire image detection research efforts [17], [23], [29].

3. Inference Pipeline

Webcam streams live frames that are preprocessed and input to the CNN. Thereby, the output is a binary probability of fire/nonfire, compared against a tuned threshold. Some other real-time detection implementations similar to this approach are represented in [5], [17], [25].

D. Random Forest Model Implementation

1. Dataset & Features

The Random Forest model uses temperature, humidity, and gas concentration as input features. These features reflect environmental triggers associated with wildfire ignition as reported in [4], [8], [10], [18], [19].

2. Model Training

The model is trained on labeled risk categories; namely, Low, Medium, High. Hyperparameter tuning is conducted with respect to the number of decision trees, maximum depth, and splitting criteria to optimize classification accuracy. Training processes follow methodologies used in ML-based fire risk forecasting in [10], [18], and [20].

3. Real-Time Prediction

Incoming sensor values are fed to the model continuously. The predicted risk level is passed to the decision-fusion module. Such hybrid ML–IoT systems are commonly implemented in [12], [14], [28].

E. Communications Interface

1. Serial/Wi-Fi Data Transmission

The final decision reached by the Python program shall be sent to NodeMCU via:

- Serial Communication for Wired Interface
- Wi-Fi communication to deploy wirelessly.
- Wi-Fi is recommended for remote alerting in modern IoT wildfire systems in [21], [22].

2. Response Handling

This came upon making the decision:

- The colored LED indicates the risk status of it in color-code.
- It triggers the buzzer in an alert condition.

These real-time responses follow the architecture of embedded alerting systems described in [1], [9], [14].

F. Decision Fusion Module

The integration logic combines:

- CNN output: fire likelihood
- Random Forest - Output from risk level

Rules:

- Fire detected OR High risk → Alert
- Fire detected AND High risk → Critical Alert

Fusion-based multimodal detection is consistent with strategies documented in [20], [23], [28], [30].

G. Deployment and Testing Environment

1. Hardware Setup

The prototype is tested indoors and outdoors under controlled lighting, temperature, and smoke conditions.

2. Test Scenarios

Multiple scenarios were considered, which included: In view of a visible flame Smokeserver artificiel High temperature–low humidity conditions Normal conditions of the environment These testing protocols align with evaluations in fire detection literature [5], [6], [18], [23], [29].

6. RESULTS AND DISCUSSION

The performance of the proposed AI-empowered forest fire detection and early risk prediction system was assessed by extensive testing of its CNN-based visual detection model, Random Forest environmental risk classifier, and IoT-enabled alerting prototype. The results reflect a high accuracy, low latency, strong sensor stability, and reliable multimodal decision-making. Observations are well aligned with performance trends in modern wildfire detection systems found in [5], [6], [12], [17], [20], [23], [28] that confirm the efficiency of integrating AI with IoT for real-time monitoring of wildfires.

A. CNN Fire Detection Performance

The transfer-learned CNN model showed excellent accuracy in distinguishing between fire and non-fire frames.

Fig3. Fire & Non-Fire Frames

1. Accuracy Metrics

- Accuracy: 97.2%
- Precision: 95.8%
- Recall (Sensitivity): 96.4%
- F1-Score: 96.1%

These results are comparable to the state-of-the-art CNN- and YOLO-based models presented in [5], [6], [15], [17], [23], [25], with accuracies ranging between 93% and 98%. The proposed model demonstrated a good ability to properly detect flames for a wide range of light conditions and backgrounds, similar to robust results found in [29].

2. Real-Time Detection Latency

- Average per-frame inference time: 0.08 seconds
- Low detection latency: <1 second end-to-end

It enables the discussion of near real-time performance, which in turn fits with lightweight architectures at edge devices in [18], [29].

B. Environmental Risk Prediction Using Random Forest

The Random Forest classifier yielded reliable predictions for Low, Medium, and High fire risk levels.

1. Prediction Accuracy

- Overall classifier accuracy: 94.6%
- High-risk detection accuracy: 92.1%

These results agree with the performance of ML models used in environmental fire risk forecasting in [4], [8], [10], [18], and [20], where Random Forest outperforms SVM and Logistic Regression repeatedly in handling nonlinear fire-related variables.

2. Sensor Stability and Response

- MQ-135 also provided responsive detection of fluctuation in air quality, consistent with sensor evaluations in [12], [14] and [28].
- DHT11 recorded correct temperature-humidity variations under controlled heating scenarios.
- It reliably detected risky conditions leading to artificially induced smoke, confirming the sensor–model synergy emphasized in [20, 28].

C. Analysis on IoT Alert System

1. Response Time

- NodeMCU response after receiving model output: < 200 ms
- These alerts caused the near-instant on-activation of an LED and a buzzer.
- These response times fall within the expected values for IoT-enabled systems to be used in early warning frameworks as described in [1], [9], [14], [21], and [22].

2. Alert Accuracy

The alerting system fired as expected in:

- 100% of fire-detected scenarios
- 96% of the high-risk environmental scenarios
- 0% false alarms under normal conditions

These values correspond to the performance of well-tuned IoT fire detection systems in [1], [9], [21].

D. Decision Fusion Analysis

The fusion approach significantly reduces false positives compared to individual model outputs.

1. Fusion Performance

- False Positive Reduction: 27% compared to vision-only models
- Reduced false negatives by 18% from sensor-only prediction. In general, the reliability of multi-modal detection agrees with the results in [20, 23, 28, 30], where the fusion of visual and environmental signals enhances robustness.

2. Critical Alert Detection

If abnormal conditions were identified using both models, a Critical Alert was raised by the system to improve situational awareness and reduce missed detections

E. System Strengths and Limitations

1. Strengths

- High real-time detection accuracy.
- Low latency suitable for deployment.
- Robust multi-sensor fusion.
- Cost-effective and scalable architecture.

2. Limitations

- Actually, heavy fog/rain visibility affects webcam-based detection greatly, as reported similarly in [3], [16] and [26].
- The MQ-135 sensor may require calibration in outdoors-forest conditions.
- Limitedtesting under extereme meteorological variations.

7. CONCLUSION

It proposes an integrated, AI-powered forest fire detection and early risk prediction system by fusing CNN-based visual detection with Random Forest–based environmental risk classification and IoT-enabled real-time alerting. Actually, the proposed multimodal architecture copes well with the main drawbacks of classical systems for monitoring forest fires that include delayed detection, low spatial resolution, and a large reliance on human intervention, as can be evidenced from previous studies [3], [4], [7], [11], [16], [26]. The implementations demonstrate that the proposed transfer-learning CNN model detects flames and smoke with promising accuracy, considering low latency, hence fulfilling the state-of-the-art deep learning approaches presented in [5], [6], [15], [17], [23], and [29]. Random Forest also predicted fire risks associated with environmental parameters highly accurately, further corroborating ML-based wildfire prediction studies presented in [4], [8], [10], [18], [20], and [28]. Finally, efficient continuous environmental monitoring is enabled upon implementing DHT11 and MQ-135 sensors with NodeMCU ESP8266 microcontrollers by following the trends within IoT-based fire detection frameworks proposed in [1], [9], [12], [14], [21], and [22]. In fact, the mechanism of decision fusion raises overall reliability in detection by fusing visual and environmental intelligences to minimize false positives, hence enhancing early warning capability. Such are also demonstrated in cases involving the multimodal wildfire detection systems of [20], [23], [28], and [30]. Such a system would be scalable, cost-effective, and robust for real-time monitoring of wildfires, besides being highly feasible for deployment into remote forest areas where conventional infrastructures are seriously limited. Though the performance of the prototype seems promising in controlled conditions, other features, like LoRa/GSM long-range communication technologies, drone-based image capture, and satellite data, might also be integrated in further works, as was done for the most advanced monitoring systems in [16], [26], [27], [30]. Enhancements of practical effectiveness can be further guaranteed, for example, by enlarging the dataset, improving outdoor sensor calibration, and deploying the system in diverse real-world environments. In general, the proposed system meaningfully contributes to various global efforts in intelligent wildfire prevention and environmental protection by showing that fusing AI, ML, DL, IoT, and sensor networks significantly increases early detection accuracy and response times that reduce the impacts of wildfires and contribute toward sustainable forest conservation.

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