FOREST FIRE PREDICTION AND WILDLIFE PROTECTION SYSTEM

[1]U. Pavan Kumar, [2]S. D. Srinivasulu, [3]V. Pothuraju, [4]V. Ratna Raju, [5]P. Ganesh, [6]P. Kumar,
[1,2,3,4,5]U. G Student, Dept ELECTRONICS AND COMMUNICATION ENGINEERING, St.Ann's College of Engineering and Technology (Autonomous), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India
[6] Assistant Professor, Dept ELECTRONICS AND COMMUNICATION ENGINEERING, St.Ann's College of Engineering and Technology (Autonomous), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India

ABSTRACT

Forest fires pose a significant threat to natural ecosystems, wildlife, and human life, causing extensive environmental and economic damage every year. Early detection and timely response are essential to minimising these losses. This project proposes an IoT-based Forest Fire Prediction and Wildlife Protection System that continuously monitors environmental parameters to identify potential fire hazards at an early stage. Sensors such as infrared (IR) sensors, fire sensors, and gas sensors are deployed in forest areas to collect real-time data. This data is processed by a microcontroller and transmitted wirelessly to a cloud platform for further analysis and prediction. Forests are vital to the planet as they provide food and shelter for many animals. One of the greatest challenges facing humans, animals, and plants is the occurrence of forest fires, which cause severe harm to wildlife, the environment, and living beings. Therefore, the ability to detect or predict forest fires early is a fundamental requirement for reducing environmental damage and protecting biodiversity. This system aims to enhance forest conservation efforts by enabling rapid response to fire threats, ultimately safeguarding ecosystems and human communities.

KEYWORDS: ***Forest fire prediction system, Raspberry Pi Pico W, Gas Sensor (MQ2), Fire Sensor, IR Sensor, Buzzer, GPS Module, LEDs (Red, Green, Yellow), IOT cloud system (Thingspeak), Software tools are C++, Arduino IDE, IOT***

INTRODUCTION

Forests are one of the most valuable natural resources on Earth and play a crucial role in maintaining ecological balance and environmental stability. They regulate climate, absorb carbon dioxide, release oxygen, and support biodiversity by providing habitat, food, and shelter to countless plant and animal species. Forests also contribute significantly to soil conservation, water cycle regulation, and prevention of natural disasters such as floods and landslides. Human civilization depends heavily on forests for resources, livelihood, and environmental sustainability, making their protection a global priority. Despite their immense importance, forests are continuously threatened by various natural and human-induced factors. Among these threats, forest fires are one of the most destructive and uncontrollable disasters. Forest fires can occur naturally due to lightning, prolonged drought, extreme temperatures, and low humidity conditions. However, a significant number of forest fires are caused by human negligence, such as unattended campfires, discarded cigarette butts, illegal logging, agricultural activities, and intentional burning. Once ignited, fires can spread rapidly due to wind and dry vegetation, causing extensive damage within a short period. Forest fires have severe consequences on ecosystems, wildlife, and human life. Large areas of vegetation are destroyed, leading to habitat loss for animals and birds. Many wildlife species are injured or killed during fires, while others are forced to migrate, disrupting ecological balance. Forest fires also destroy breeding grounds and food sources, posing a serious threat to endangered species. The long-term impact includes reduced biodiversity and degradation of natural habitats. In addition to ecological damage, forest fires significantly affect the atmosphere and human health. The burning of vegetation releases large quantities of carbon dioxide, carbon monoxide, and particulate matter into the air, contributing to air pollution and global warming. Smoke from forest fires spreads over long distances, reducing visibility and causing respiratory problems such as asthma and bronchitis. Forest fires also weaken soil fertility by destroying organic matter, increasing the risk of soil erosion, floods, and landslides, thereby affecting agricultural productivity and water resources.

LITERATURE SURVEY

Wildfires are increasing in frequency, extent and societal impact due to climate change and land-use change; they destroy habitat, injure wildlife populations, and reduce the effectiveness of conservation efforts. Predictive systems that combine environmental forecasting (fire risk/occurrence/duration) with wildlife detection and monitoring can enable earlier mitigation, targeted evacuations of animals, and more effective post-fire recovery planning.

Data sources used across studies: Meteorological & climate data: temperature, relative humidity, wind, precipitation, drought indices (e.g., FWI), often from national meteorological services or reanalysis products. Remote sensing/satellite imagery: MODIS, VIIRS, Sentinel (optical and SAR), land cover maps, vegetation indices (NDVI, EVI). These supply both ignition indicators (hotspots) and fuel-condition proxies. Topography: elevation, slope, aspect derived from DEMs (affect fire spread).

Human / socio-economic: proximity to roads/settlements, land-use, agricultural burning records — commonly used to model ignition probability. Wildlife monitoring data: camera traps, acoustic sensors, GPS collars/telemetry, and aerial surveys (drone imagery) for animal presence, movement, and post-fire impacts.it approaches Statistical/classical models: logistic regression and hazard models are common baselines for ignition probability and susceptibility mapping. Tree-based ensemble models: Random Forest, Gradient Boosting, and XGBoost are widely used for susceptibility mapping and short-term prediction because of good performance on tabular environmental features. Deep learning: CNNs (for imagery), RNNs / LSTMs (for time series), and hybrid architectures (CNN + LSTM) have been applied to fuse satellite images with meteorological time series. Newer transformer-based spatio-temporal models are emerging in recent reviews. Hybrid & AutoML approaches: Pipelines that combine domain-specific feature engineering with automated model selection (AutoML) have shown promise for scalable, low-bias fire-prediction systems.

Wildlife protection & conservation methods (integrated with fire prediction) : Detection & monitoring: Deep learning on camera-trap and aerial imagery (object detection / instance segmentation) and automated bioacoustics classification detect species presence and behavior relevant to risk (e.g., congregation near human settlements). These allow rapid mapping of wildlife locations relative to fire risk. Tracking & alerts: GPS collar / telemetry data fed into movement models identify escape corridors and bottlenecks; combined with fire-spread forecasts, they enable routing and targeted rescue or temporary refuges. IoT & edge sensing: Acoustic sensors, low-power cameras and edge ML models provide near-real-time alerts for both fires and animal distress near fire lines. Case studies report high detection accuracy for prototype systems. Typical preprocessing & feature engineering Spatial aggregation & gridding: convert point/patch data to consistent spatial grids (e.g., 1 km). Temporal windows: use lagged meteorological features (past 3–14 days), moving averages for dryness/fuel accumulation. Handling imbalance: downsampling, SMOTE/oversampling, cost-sensitive learning because fire occurrence is rare relative to non-fire days. Fusion: classical concatenation of tabular features with CNN-extracted imagery features or late fusion via ensemble stacking.

EXISTING SYSTEM

In the existing forest fire monitoring framework, most systems are designed with a reactive approach, where action is taken only after the fire has already occurred. Forest fire management traditionally depends on human observation, where forest guards patrol assigned regions on foot or using vehicles. These patrols are scheduled periodically and are limited by manpower, accessibility, and terrain conditions. In dense forests and mountainous regions, regular patrolling becomes extremely difficult, resulting in large unmonitored areas.

Watch towers are another important part of the traditional monitoring system. These towers are placed at elevated locations, allowing guards to visually inspect forest regions for smoke or flames. However, this method relies entirely on line-of-sight visibility, which is often obstructed by dense vegetation, fog, or low light conditions. During nighttime, early morning, or adverse weather conditions, fire detection becomes highly unreliable.

Satellite-based forest fire detection systems are also widely used in modern forest management. These systems monitor forest regions using thermal imaging and infrared data to identify abnormal heat patterns. While satellites can cover large geographical areas, they suffer from several limitations. Satellite images are not available continuously and depend on orbital schedules. Fires that start between satellite passes may go undetected for several hours. Additionally, cloud cover and heavy smoke reduce image clarity, leading to delayed or false detections.

In certain locations, basic electronic fire detection systems are implemented using simple sensors. These systems are usually installed near forest boundaries or sensitive zones. However, such systems detect fire only when flames or smoke reach a certain intensity. Since they do not analyze gradual changes in environmental conditions, early-stage fire detection is not possible.

Existing systems also lack intelligent data processing capabilities. Most systems operate on predefined threshold values and do not adapt to seasonal variations, climate changes, or forest-specific characteristics. There is no provision for storing historical data or performing trend analysis to understand fire patterns.

PROPOSED SYSTEM

The proposed Forest Fire Prediction and Wildlife Protection System is designed as a proactive and intelligent solution that continuously monitors forest conditions and provides early warnings before fire situations become critical. The system is based on Internet of Things (IoT) technology, which enables real-time data collection, remote monitoring, and intelligent decision-making. In this system, fire sensors are strategically deployed across forest regions to detect the presence of flames at an early stage. These sensors are capable of identifying even small fire sparks, enabling immediate detection before the fire spreads extensively. Alongside fire sensors, MQ-2 gas sensors are used to detect smoke and combustible gases such as carbon monoxide and methane. Gas detection plays a vital role in identifying fire risks during the initial phase, even before visible flames appear. To address wildlife safety, IR sensors are incorporated into the system to detect animal movement. These sensors help identify the presence and movement of animals near fire-prone areas. The collected data support forest authorities in planning wildlife evacuation and rescue operations during fire emergencies, significantly reducing animal casualties.

A Raspberry Pi serves as the central processing unit of the proposed system. It collects data from all sensors, processes it in real time, and evaluates the severity of the detected conditions. The Raspberry Pi continuously compares sensor readings with predefined safety thresholds and logical conditions. When abnormal patterns such as smoke presence, gas concentration, or flame detection are observed, the system immediately triggers local alerts using buzzers and LED indicators. The system also transmits sensor data to an IoT cloud platform, allowing forest officials to monitor conditions remotely. Through the cloud interface, authorities can view real-time sensor values, alert notifications, and system status from any location. All sensor data is stored securely in the cloud for future analysis, reporting, and decision-making.

One of the most important features of the proposed system is its fire prediction capability. By analyzing historical sensor data and identifying recurring patterns, the system can estimate the probability of fire occurrence in specific regions. This predictive analysis enables authorities to take preventive actions such as increasing patrol frequency, restricting human access, and preparing firefighting resources in advance.

ARCHITECHTURE

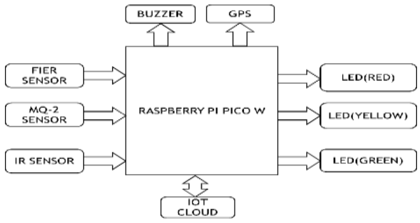

Fig 1: Block Diagram

METHODOLOGY DESCRIPTION

A. Data Acquisition: Environmental data is collected from multiple input sensors. A Fire Sensor is likely a flame or fire sensor that detects the presence of fire. An MQ-2 Sensor detects gas concentrations, which can indicate smoke or combustible gases. An IR Sensor can detect heat signatures.

B. Central Processing Unit: The data from these sensors is fed into a Raspberry Pi Pico W, which acts as the central processing unit. This unit likely runs logic to analyse the sensor inputs and determine if a fire condition is met.

C. Output and Alerting: Based on the processing, the Raspberry Pi Pico W triggers various output devices for local alerts. LEDs (Red, Yellow, Green) provide visual status indicators (e.g., green for safe, yellow for caution, red for fire detected). A Buzzer provides an audible alarm when a fire is detected.

D. Connectivity and Communication: The system utilises connectivity modules for remote monitoring and location tracking. A GPS module provides the precise location coordinates of the system. Data, including sensor readings and GPS location, is transmitted to an IOT Cloud platform for remote monitoring, analysis, and further action.

HARDWARE AND SOFTWARE REQUIREMENTS

Raspberry Pi Pico W:-

Fig 2.1: Raspberry Pi W

The Raspberry Pi Pico W is a low-power microcontroller board designed for IoT, featuring built-in 2.4GHz Wi-Fi (802.11n) and Bluetooth 5.2 (BLE) via the Infineon CYW43439 chip. Powered by the RP2040 chip, it excels at acting as a wireless sensor node, web server, or MQTT client in smart home and industrial IoT, typically programmed using Micro Python or C/C++.

Networking: Seamlessly connects to Wi-Fi networks and supports WPA3 security.

Web Server/Broker: Can act as a web server to host dashboards or connect to platforms via MQTT for real-time monitoring.

Peripherals: Includes 26 GPIO pins, ADC (for analogue sensors), I2C, SPI, and UART, enabling interface with numerous sensors. Low Power: Efficient for battery-powered applications.

Software Support: Strong library support for MicroPython, including network and uMQTT libraries.

Fire Sensor:-

Fig 2.2: Fire Sensor

Forest fire prediction systems utilise networks of IoT-enabled sensors (temperature, humidity, gas/smoke, flame) to detect early fire signs, often achieving over 97% accuracy. These sensors, placed in high-risk areas, monitor environmental parameters to detect anomalies, sending real-time alerts via Wi-Fi or GSM to forestry teams. Modern systems use AI and solar power to boost reliability and sustainability.

GAS SENSOR

Fig 2.3: Gas Sensor

The MQ-2 sensor is a low-cost, 5V metal oxide semiconductor (MOS) sensor used in forest fire prediction systems to detect smoke, methane, propane, and carbon monoxide. It acts as a fire indicator by measuring gas concentration changes (300-10000ppm), sending analog or digital signals to microcontrollers (e.g., Arduino/ESP32) for real-time alerting via IoT.

IR Sensor

Fig 2.4: IR sensor

Infrared (IR) sensors in forest fire prediction systems detect thermal radiation emitted by flames and hot gases, enabling early detection of fire signatures, even at night or through smoke. These sensors, often integrated with IoT devices, identify heat intensity to trigger immediate alerts, aiding in rapid response and preventing small blazes from becoming uncontrollable.IR sensors, specifically photodiode-based flame sensors, detect the unique infrared light signature (thermal radiation) produced by fire. Mid-Wave Infra-Red (MWIR, 3–5) range is most effective for detecting high-temperature vegetation fires, while Long-Wave Infrared (LWIR, 8–14) is used for improved identification. They can detect fire before thick smoke is visible, often catching fires when they are still small, low-visibility, or in remote areas.

GPS Module

Fig 2.5: GPS Module

GPS modules in forest fire prediction systems provide real-time, precise geographical coordinates (latitude and longitude) of fire outbreaks, allowing authorities to locate and combat fires promptly. Often, sensors (like Neo 6M or LoRa/GPS HAT) are integrated with microcontrollers like ESP32/NodeMCU to send location data via SMS or IoT platforms. When sensors (flame, smoke, IR) detect a fire, the GPS module activates to retrieve exact location data from satellites.The system sends this location, along with fire status updates, directly to forest officials' phones or dashboards via GSM modules. The NEO-6M GPS module is frequently used due to its accuracy in identifying longitude and latitude.GPS modules are typically coupled with microcontrollers such as Arduino or NodeMCU (ESP8266) and sensors to create an IoT-based system. The system can be used to track the movement of a fire front in real-time, aiding in quick containment.

Buzzer

Fig 2.6: Buzzer

In forest fire prediction and detection systems, a buzzer (or beeper) serves as a critical local alert component within Internet of Things (IoT) frameworks. It acts as a mechanical or electromechanical acoustic signalling device designed to provide immediate audio notification when environmental sensors detect signs of fire. When sensors (such as flame, smoke, or temperature sensors) detect that heat or gas levels have exceeded a pre-set threshold, the microcontroller (e.g., Arduino or

NodeMCU) triggers the buzzer to sound an alert.

It alerts nearby personnel, forest rangers, or wildlife in the immediate vicinity of the fire to act immediately, even if the central control unit hasn't yet received the data. In cases where the internet connectivity is slow or down, and SMS alerts (via GSM) are delayed, the buzzer acts as a reliable on-site notification system. The buzzer is programmed to sound continuously until the fire is brought under control and the sensor values return to normal, non-hazardous levels.

LEDs

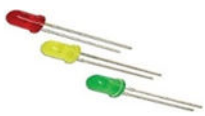

Fig 2.7: LED (Red, Yellow, Green)

Different colored LEDs, such as red, yellow, and green, help users quickly understand the system state. LEDs operate on the principle of electroluminescence, in which electrons recombine with holes in a semiconductor material and emit light. The colour of the LED depends on the semiconductor material used. Green LEDs generally indicate normal or safe conditions, yellow LEDs represent warning or moderate risk levels, and red LEDs signal danger or fire detection. Because LEDs require low voltage and current, they are suitable for battery-powered and remote monitoring systems.

In forest fire detection systems, LEDs are connected to the GPIO pins of controllers such as the Raspberry Pi. The controller activates specific LEDs based on sensor readings from fire sensors, MQ-2 gas sensors, and IR sensors. For example, the green LED glows during normal conditions, the yellow LED turns on when abnormal temperature or smoke levels are detected, and the red LED lights up when fire is confirmed. Thus, LEDs provide an instant, reliable, and easy-to-understand visual alert mechanism that improves system monitoring and safety.

SOFTWARE TOOLS

A. RASPBIAN OS: Raspbian OS is a free and open-source operating system specifically designed for the Raspberry Pi family of single-board computers. It is based on Debian Linux, which provides a stable and robust foundation for running software efficiently. Raspbian is optimised to work on the limited hardware resources of Raspberry Pi, such as its CPU, memory, and storage, ensuring smooth performance even on older models. The OS comes with a desktop environment that is lightweight yet user-friendly, making it accessible for beginners as well as advanced users. Its interface resembles a typical Linux desktop, with a taskbar, application menu, and system tray, providing a familiar computing experience.

B. ThingSpeak Cloud Platform: ThingSpeak is utilised for real-time data visualisation, storage, and remote monitoring. It provides graphical dashboards to analyse variations in parameters such as the infrared sensor, the smoke sensor, the fire sensor, and the GPS latitude and longitude

D. UART Protocol: Simple asynchronous, one-to-one communication between two devices (e.g., Pico W to GPS module or PC).

And required pins and wires are TX (Transmit) and RX (Receive). Pins are usually mapped to UART0 or UART1. Its Key Features are Asynchronous (no shared clock), requires matched baud rates (typically 115,200), and full-duplex. And MicroPython uses the machine.

RESULT AND DISCUSSION

ThingSpeak Visualisation Results

The real-time sensor data acquired from the system is visualised using the ThingSpeak cloud platform. The graphical representation of parameters such as infrared sensor, smoke sensor, fire sensor, and GPS latitude and longitude enables continuous remote monitoring and analysis.

E. I2C Protocol: It is connecting multiple sensors, RTCs, or OLED displays on a shared bus. Uses two wires, SDA (Serial Data) and SCL (Serial Clock), plus GND and 3.3V. Requires pull-up resistors on data lines.

F. SPI Protocol: This is High-speed data transfer for applications like SD card readers, high-res OLEDs, or camera modules. It uses four wires: SCK (Clock), MOSI (Master Out Slave In), MISO (Master In Slave Out), and CS/SS (Chip Select).

E. Supporting Libraries: The Raspberry Pi Pico W supports specialised libraries for WiFi (network, ucryptolink), Bluetooth, and hardware interfacing (machine, uasyncio) primarily via MicroPython and C/C++. Essential libraries for IoT include umqtt, simple and umqtt. robust for MQTT, and urequest for HTTP requests.

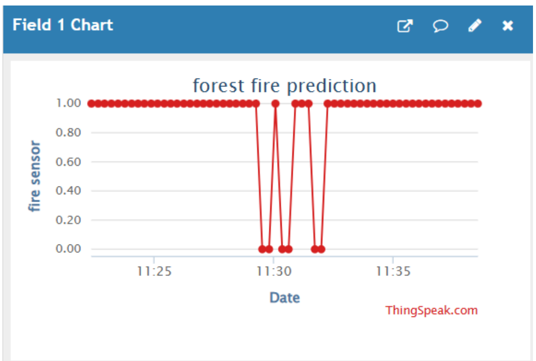

Fig 3.1: Fire Sensor

The flame sensor detects fire by sensing infrared radiation and sends a digital signal to the Raspberry Pi via a GPIO pin. The Raspberry Pi, running a Python program, checks if the fire threshold is met and activates alerts like a buzzer and red LED. It also collects GPS coordinates and uploads the fire alert and location data to the cloud using Wi-Fi and IoT platforms such as ThingSpeak or Blynk for real-time remote monitoring.

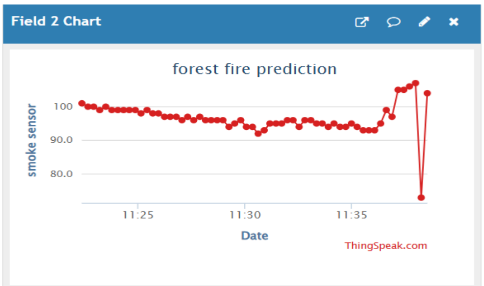

Fig 3.2: Smoke Sensor

The MQ-2 smoke sensor detects smoke or combustible gases and sends an analogue signal to the Raspberry Pi via an ADC module. If the smoke level exceeds a set threshold, the system triggers warning LEDs and a buzzer while recording the GPS location. The Raspberry Pi then uploads the alert data to the cloud through Wi-Fi and IoT platforms like ThingSpeak or Blynk for real-time monitoring.

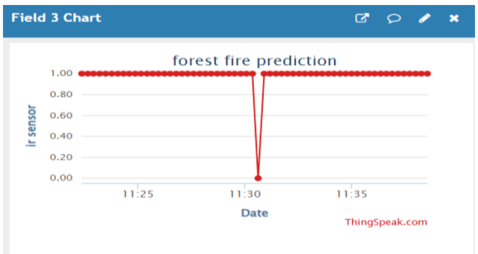

Fig 2.3: IR Sensor

The IR sensor detects wildlife movement by sensing reflected infrared radiation and sends a digital signal to the Raspberry Pi via a GPIO pin. Upon detecting movement, the system activates a yellow LED and buzzer, records the GPS location, and uploads the alert data to the cloud using Wi-Fi and IoT platforms like ThingSpeak or Blynk. This enables real-time monitoring by forest authorities.

CONCLUSION

The IoT-based forest fire prediction and wildlife protection system uses sensors like IR, fire, and MQ-2 gas sensors integrated with a Raspberry Pi to monitor forest conditions continuously. It provides early fire detection through real-time sensing and automated alerts, reducing large-scale damage and protecting wildlife habitats. GPS technology offers precise fire location data, enabling quick response by officials even in remote areas. Visual and audible alerts ensure immediate local warnings, crucial where internet access is limited. The system also aids in monitoring animal movement to prevent casualties and maintain ecological balance. With enhancements like machine learning and solar power, it can evolve into a comprehensive smart forest management solution.

FUTURE ENHANCEMENT

The proposed system can be further enhanced by the convergence of Artificial Intelligence (AI), Internet of Things (IoT) sensors, and autonomous drones, transforming conservation from a reactive to a proactive model. These technologies are expected to shift towards real-time, edge-based systems that detect threats within minutes rather than hours, significantly reducing environmental damage. Advanced AI-driven early warning systems use deep learning models like CNNs and LSTMs to analyse satellite, weather, and topographical data, achieving fire prediction accuracy with AUC above 0.94. Explainable AI (XAI) enhances these models by clarifying prediction reasons, while Digital Twin technology creates virtual forest replicas to simulate fire behaviour in real-time. Autonomous drone swarms equipped with thermal sensors will map fire fronts and perform firefighting tasks even in challenging conditions. CubeSats with on-board AI will detect smoke within 14 minutes of ignition, greatly improving detection times. Multi-modal sensor fusion combines ground IoT data on temperature, humidity, and CO2 with satellite imagery to reduce false alarms. This integrated approach provides detailed, accurate monitoring for more effective fire management.

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