"A Deep Learning Based Experiment on Forest Wildfire Detection in Machine Vision Framework."

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Abstract - Forest wildfires pose a serious threat to ecosystems, wildlife, human settlements, and natural resources. Conventional wildfire detection techniques mainly rely on sensor-based alert systems, satellite monitoring, and human observation, all of which frequently have poor coverage, slow response times, and expensive operating costs. Intelligent systems that can detect wildfire incidents in their early stages are becoming more and more necessary as the need for early detection, accuracy, and real-time monitoring grows. This project introduces A Deep Learning-Based Experiment on Forest Wildfire Detection in a Machine Vision Framework, an automated detection system with real-time monitoring and sophisticated image analysis to improve early warning capabilities.Using a variety of wildfire datasets, a convolutional neural network (CNN) model is trained to reliably separate visual characteristics associated with fires from those that are not. visual characteristics of non-fire elements like fog, clouds, and sunlight. Rapid wildfire event detection and classification are made possible by the system's real-time processing of visual inputs. When fire conditions are detected, a monitoring framework enables timely alert generation and supports ongoing observation.The experimental findings show how well the deep learning-based method detects wildfires in a variety of lighting and environmental circumstances. This project demonstrates how machine vision and artificial intelligence technologies can be used to convert conventional wildfire monitoring systems into intelligent, data-driven solutions. Future improvements, such as real-time geolocation mapping, integrate

Key Words: Forest Wildfire Detection, Deep Learning, Machine Vision Framework, Convolutional Neural Network (CNN), Real-Time Monitoring, Automated Early Warning System.

1.INTRODUCTION

Forest wildfires pose a great threat to the environment, wildlife, and human lives. Over the past years, the rise in global temperatures, extended dry seasons, and most human activities have increased the occurrence and magnitude of wildfires. Early detection of forest wildfires plays an important role in reducing damage and allowing timely action by forest and disaster management authorities. The major drawbacks of traditional wildfire detection methods include delayed response, high operational costs, limited real-time monitoring capability, and dependency on weather conditions. Most of the traditional wildfire detection methods, such as manual surveillance, watchtowers, and satellite monitoring systems, suffer from these drawbacks. They cannot detect forest wildfires in the early stages, especially in large and dense forest regions.

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2. Body of Paper

Forest wildfires pose a serious threat to environmental sustainability and human safety. Conventional fire detection techniques rely on manual surveillance and sensor-based systems, which often suffer from delayed response and limited coverage. Section 1 presents the motivation and objectives of the proposed system.

Figure 1 illustrates the role of wildfire detection in environmental protection and disaster management. The need for intelligent monitoring systems has led to the adoption of deep learning techniques for early wildfire detection.

System Requirements

Section 2 describes the functional and non-functional requirements of the proposed system. In Sec. 2.1, requirement modelling is discussed, focusing on system inputs, outputs, and constraints.

Table 1 lists the functional requirements, while Table 2 presents the non-functional requirements such as scalability and reliability. Section 2.3 details the hardware requirements, including the ESP32 microcontroller, temperature sensor, gas sensor, and flame sensor.

Figure 3 shows the ESP32 microcontroller used in the system, and Fig. 4 illustrates the temperature and humidity sensor (DHT11).

System Design

Section 3 explains the overall system design and architecture. The block diagram of the fire detection system is shown in Fig. 2. The architecture integrates sensor data with image-based analysis for accurate fire detection.

In Sec. 3.2, Unified Modeling Language (UML) diagrams are presented to describe system behavior. Figure 11 represents the use case diagram, while Fig. 12 shows the UML activity diagram. Section 3.3 contains the object diagram illustrating object interactions.

Implementation

Section 4 describes both software and hardware implementation. Section 4.1 explains the software implementation using a Convolutional Neural Network (CNN) for wildfire detection. After the first occurrence, CNN is used throughout the paper.

Section 4.2 focuses on hardware implementation. Figure 15 shows the hardware implementation, and Fig. 16 presents the complete project hardware setup.

Testing

Section 5 discusses system testing and evaluation. In Sec. 5.2, test case design is explained, and testing results are presented in Sec. 5.3.

Figure 18 shows the hardware test results, while Fig. 19 displays the software results obtained during testing.

Results

Section 6 presents the final results of the system. The proposed model demonstrates accurate wildfire detection under different environmental conditions with minimal false alarms.

Table -1: Hardware and Software Configuration

Hardware Component	Description	Function
ESP32 Microcontroller	Dual-core 240 MHz, built-in Wi-Fi and BLE	Main controller for sensor data acquisition, processing, and network communication
DHT11 Sensor	Digital temperature and humidity sensor	Monitors ambient forest temperature and humidity
MQ2 Gas Sensor	Detects smoke and flammable gases	Provides early indication of fire or combustion
P103 Flame Sensor	Infrared flame detection sensor	Confirms presence of fire
Camera Module	Standard USB/IP camera	Captures images/video for deep learning-based fire detection
Jumper wires / Breadboard / PCB	Physical wiring infrastructure	Ensures secure interconnection of components
Optional Solar Panel / Battery Backup	Energy source for remote deployment	Ensures continuous operation in forest environments
Power Supply Module	5V regulated or battery backup	Provides stable power to sensors, ESP32, and camera

The hardware setup involved in the Forest Wildfire Detection System comprises the main processing unit (ESP32), sensing devices (DHT11, MQ2, and P103), camera module, and the power modules. All these hardware modules are vital for the effective and continuous monitoring task performed by the forest wildfire detection system for early prevention.

Performance of the system relies on the appropriate selection of hardware components. The selected hardware meets the objectives of having a reliable system, a real-time system, and an efficient power system for the forest environment. ESP32 extracts data from the environmental sensors and initiates notifications through the cloud and Telegram. The camera on the laptop for image capture for the machine vision wildfire detection system eliminates the need for the camera component.

Fig -1: ESP32 Microcontroller

Fig-2: Temperature and Humidity Sensor

Fig-3: Flask Web Dashboard

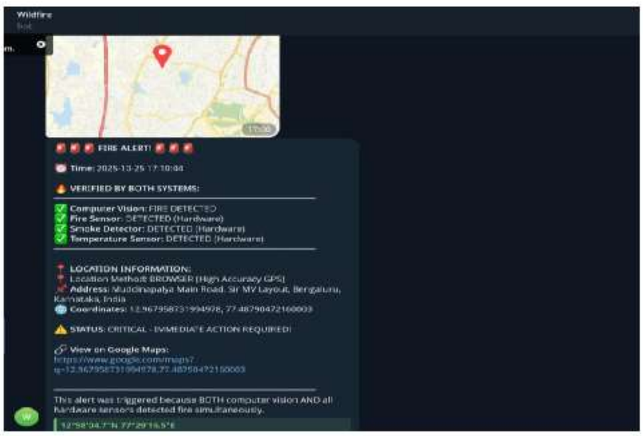

Fig-4: Telegram Bot API

3. CONCLUSIONS

The development and implementation of the IoT-based Forest Wildfire Detection System demonstrate the feasibility and practical value of integrating modern sensing technology, real-time environmental monitoring, wireless communication, and cloud-assisted data analytics in forest management and wildfire prevention. The project successfully achieves its primary objective of providing continuous monitoring of temperature, smoke, gas concentration, and flame presence to ensure early detection of wildfire hazards. Through the combination of ESP32 microcontroller, temperature, MQ135 gas, and flame sensors, camera-based fire detection modules, Blynk cloud interface, and Telegram alert notification services, the system offers an autonomous and intelligent approach to wildfire monitoring, reducing dependency on human patrols and enhancing operational transparency.

The results indicate that the system provides accurate, stable, and reliable measurements under extended operational conditions and demonstrates strong responsiveness to sudden environmental variations. The implementation proves that early wildfire detection is achievable by monitoring temperature spikes, smoke emission levels, and visual flame indicators, offering significant advantages over conventional observation methods that rely solely on periodic human inspections. The project accomplishes its goal of delivering real-time alerts to authorities whenever critical conditions occur, enabling rapid response and mitigating risks of environmental damage, property loss, and threats to human and animal life.

The completed system demonstrates the potential and importance of IoT in transforming conventional forest management practices into intelligent, adaptive monitoring ecosystems. The system enhances situational awareness, improves resource allocation efficiency, and contributes to environmental protection by enabling early interventions that prevent small fires from escalating into large-scale wildfires. The research confirms that IoT-enabled remote access and data-driven decision-making capabilities can substantially improve the effectiveness of forest fire management in both remote and densely forested areas.

The conclusion drawn from this development emphasizes that real-time environmental transparency is critical to ensuring effective wildfire prevention. The smart system enables early fire detection, which is a major improvement over conventional methods where fires are typically identified only after visible smoke or flame is observed. This research project highlights the broader societal relevance of IoT-based wildfire detection systems, particularly in regions where wildfire risk is high and environmental or economic losses are severe. The integration of cloud connectivity extends accessibility far beyond physical observation points, granting authorities remote insight and decision power regardless of location. Such connectivity aligns with contemporary smart-environment initiatives, representing a transition from reactive fire management to proactive risk mitigation.

The work undertaken in this project reinforces the importance of IoT and automation technologies as essential components of future environmental monitoring solutions. The project validates that IoT driven wildfire detection systems can enhance sustainability, improve disaster management, and support modern forest protection initiatives. Overall, the Forest Wildfire Detection System successfully fulfills project objectives and demonstrates significant potential for widespread real-world adoption.

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