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Research Paper

Fire Detection Using Raspberry Pi

[1]Mukkala Mary prashanthi, [2]Dr. G. Harish Kumar

[1]M. Tech Student, Dept of ECE, MALLA REDDY ENGINEERING COLLEGE FOR WOMEN, Maisammaguda, Dhulapally, Kompally, Secunderabad-500100, Telangana, INDIA.
[2]Assistant professor, Dept ECE, MALLA REDDY ENGINEERING COLLEGE FOR WOMEN, Maisammaguda, Dhulapally, Kompally, Secunderabad-500100, Telangana, INDIA.

ABSTRACT

The AI Based Fire Detection and Prediction System is an intelligent safety solution designed to detect fire incidents at an early stage and predict potential fire hazards before they become severe. The system combines Artificial Intelligence (AI), Internet of Things (IoT), and multi-sensor technology to continuously monitor environmental conditions. Various sensors such as flame, smoke, gas, sound, vibration, and LDR sensors collect real-time data, which is processed using Raspberry Pi 5. AI algorithms and Convolutional Neural Networks (CNNs) analyze sensor readings and camera images to identify fire-related patterns with high accuracy. The system performs sensor fusion to reduce false alarms and improve reliability. When a fire is detected, immediate alerts are sent through IoT communication channels, while a buzzer provides local warnings. Predictive analytics further help identify potential fire risks based on environmental trends. The proposed system enhances safety, minimizes property damage, improves emergency response time, and provides a cost-effective solution for residential, industrial, forest, and smart city applications.

Keywords: Artificial Intelligence (AI), Internet of Things (IoT), Fire Detection, Fire Prediction, Raspberry Pi 5, CNN, Sensor Fusion, Flame Sensor, MQ135 Sensor, Real-Time Monitoring.

INTRODUCTION

Fire accidents are among the most dangerous disasters that threaten human lives, infrastructure, and the environment. Traditional fire detection systems generally depend on smoke detectors and heat sensors that operate using fixed threshold values. These systems often generate false alarms due to environmental disturbances such as dust, humidity, and cooking smoke. With the rapid development of Artificial Intelligence and Internet of Things technologies, modern fire detection systems have become more intelligent and reliable. The proposed AI Based Fire Detection and Prediction System utilizes multiple sensors and camera-based monitoring to detect fire hazards accurately. Raspberry Pi 5 serves as the central processing unit that collects and processes sensor data in real time. The system integrates flame, gas, sound, vibration, and LDR sensors to monitor different environmental parameters simultaneously. AI algorithms and CNN models analyze the collected information and detect patterns associated with fire incidents. Sensor fusion techniques improve the decision-making process by combining multiple inputs. The integrated camera module provides visual confirmation of fire and smoke conditions. Once a fire event is confirmed, alerts are transmitted through IoT communication channels, enabling rapid response. The system also predicts future fire risks based on environmental trends.

LITERATURE SURVEY

Several researchers have contributed to the development of intelligent fire detection systems using IoT, wireless communication, and machine learning technologies. Early fire detection systems primarily relied on smoke and temperature sensors that triggered alarms when predefined thresholds were exceeded. Although effective in basic applications, these systems often suffered from high false alarm rates and limited monitoring capabilities. Recent advancements in IoT have enabled real-time environmental monitoring through interconnected sensor networks. Researchers introduced wireless fire detection systems that utilize cloud platforms for data storage and remote monitoring. Machine learning techniques have further improved fire detection accuracy by analyzing complex patterns in sensor data. Deep learning models such as Convolutional Neural Networks have been widely used for image-based fire and smoke recognition. Studies have demonstrated that combining sensor data with computer vision significantly enhances reliability and reduces false detections.

EXISTING SYSTEM

Traditional fire detection systems mainly depend on standalone smoke detectors, heat sensors, and manual alarm mechanisms. These systems operate using threshold-based detection methods, where alarms are activated when specific sensor values exceed predefined limits. Although widely adopted, they often generate false alarms due to smoke from cooking activities, dust particles, or environmental variations. Most conventional systems monitor only a single parameter and cannot differentiate between actual fire hazards and harmless conditions. Some advanced systems offer remote monitoring through IoT platforms, but their decision-making capabilities remain limited. Camera-based fire detection systems have also been introduced, but they require high computational resources and continuous internet connectivity. Existing systems generally lack sensor fusion and predictive capabilities. They cannot effectively analyze multiple environmental conditions simultaneously. Additionally, most systems rely on centralized processing and manual intervention after fire detection. These limitations reduce reliability, increase operational costs, and delay emergency response actions.

PROPOSED SYSTEM

The proposed AI Based Fire Detection and Prediction System integrates IoT, Artificial Intelligence, and multi-sensor fusion technologies for accurate and real-time fire monitoring. Raspberry Pi 5 acts as the central controller that collects data from flame, MQ135 gas, LDR, sound, and vibration sensors. A camera module continuously captures images for visual analysis. The system employs CNN-based image processing techniques to identify fire and smoke patterns with high accuracy. Sensor fusion combines information from multiple sensors to reduce false alarms and improve reliability. When abnormal conditions are detected, AI algorithms validate the fire event before issuing alerts. The system immediately activates a buzzer and sends notifications through IoT communication networks. Live video streaming and GPS-tagged alerts provide additional situational awareness. Predictive analytics help identify fire risks before actual ignition occurs. The proposed solution offers high accuracy, fast response time, low power consumption, and scalability for various environments.

ARCHITECTURE

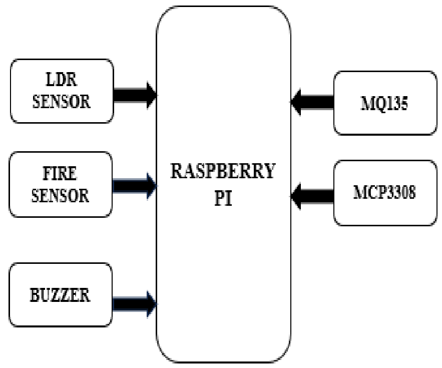

Fig: 1 Architecture of Fire Detection Using Raspberry Pi

The architecture of the proposed system consists of three major layers: sensing, processing, and communication. The sensing layer includes flame sensors, MQ135 gas sensors, LDR sensors, sound sensors, vibration sensors, and a camera module that continuously monitor environmental conditions. These sensors collect real-time data and transmit it to the Raspberry Pi 5. The processing layer consists of AI algorithms and CNN models that analyze sensor readings and image data. Sensor fusion techniques combine multiple inputs to improve decision accuracy and eliminate false alarms. The camera captures visual evidence for fire confirmation. The communication layer utilizes Wi-Fi and MQTT protocols to transmit alerts, live video streams, and sensor information to users. A buzzer serves as a local alert mechanism. The architecture supports real-time monitoring, intelligent analysis, and rapid emergency response while maintaining low power consumption and scalability.

MEDHOLOGY DISCRIPTION

The methodology begins with continuous environmental monitoring using flame, MQ135 gas, LDR, sound, and vibration sensors. These sensors collect real-time data related to temperature, smoke concentration, flame intensity, light variation, sound patterns, and structural disturbances. The collected data is transmitted to the Raspberry Pi 5 for processing. Initially, threshold-based analysis is performed to identify abnormal conditions. If sensor readings exceed predefined limits, the system generates a preliminary warning. Simultaneously, the camera module captures images and video streams of the monitored area. AI-based CNN models analyze these images to detect fire and smoke characteristics. Sensor fusion techniques combine information from all sensors and camera outputs to validate the fire event. The AI model compares real-time observations with pre-trained datasets containing fire and non-fire samples. Once a fire is confirmed, the system activates a buzzer and sends notifications via Wi-Fi and MQTT protocols. Alerts include timestamps, sensor information, GPS coordinates, and captured images. The system also stores historical data for predictive analysis. Machine learning algorithms analyze trends and identify potential fire risks before ignition occurs. This comprehensive methodology ensures accurate detection, reduced false alarms, and rapid emergency response.

HARDWARE AND SOFTWARE REQUIREMENTS

Fig: 2 Raspberry Pi

The Raspberry Pi serves as the central processing unit of the entire fire detection system. It collects data from all connected sensors and processes it in real time. The Raspberry Pi executes AI algorithms and analyzes sensor readings to determine fire conditions. It also controls the communication and alert mechanisms of the system. Acting as the system's brain, it coordinates monitoring, analysis, and response operations efficiently.

Fig:3 LDR Sensor

The LDR (Light Dependent Resistor) sensor is used to measure the intensity of light present in the environment. It helps detect sudden changes in brightness that may occur due to the presence of flames. The resistance of the LDR decreases as light intensity increases. The sensor continuously sends light-level data to the Raspberry Pi for analysis. This information assists the system in identifying abnormal lighting conditions associated with fire incidents.

Fig:4 Fire Sensor

The Fire Sensor is responsible for detecting flames by sensing infrared radiation emitted from a fire source. It acts as the primary fire detection component in the system. The sensor continuously monitors the surrounding area for flame activity. When fire is detected, it sends a signal to the Raspberry Pi for further processing. This enables the system to respond quickly and initiate safety measures.

Fig:5 MQ135 Sensor

The MQ135 sensor is used to detect harmful gases, smoke, and air pollutants in the environment. It plays an important role in identifying the presence of combustible gases that may indicate a fire hazard. The sensor provides analog output corresponding to gas concentration levels. These readings are continuously monitored by the Raspberry Pi. Early detection of smoke and gases helps prevent potential fire accidents.

Fig: 6 Buzzer

The buzzer is an output device used to provide immediate audio alerts when a fire is detected. It generates a loud warning sound to notify nearby people about the emergency. The Raspberry Pi activates the buzzer whenever abnormal fire conditions are confirmed. This helps occupants take quick action and evacuate safely. The buzzer serves as a simple yet effective local alarm mechanism in the system.

Fig: 7 MCP3308 ADC Converter

The MCP3308 is an Analog-to-Digital Converter (ADC) used to interface analog sensors with the Raspberry Pi. Since the Raspberry Pi does not have built-in analog input pins, the MCP3308 converts analog sensor signals into digital data. It supports multiple input channels for connecting various sensors. The converted digital values are processed by the Raspberry Pi for decision-making. This component ensures accurate and reliable sensor data acquisition.

RESULTS AND DISCUSSION

The proposed AI Based Fire Detection and Prediction System demonstrated excellent performance during testing and evaluation. The integration of multiple sensors and AI-based image analysis significantly improved detection accuracy compared to conventional systems. Sensor fusion techniques successfully minimized false alarms caused by environmental disturbances. The CNN model accurately identified fire and smoke patterns in real-time camera feeds. The system achieved rapid response times and generated alerts within a few seconds of fire detection. IoT communication ensured reliable transmission of notifications and live video streams. Power consumption remained low, making the solution suitable for continuous operation. Experimental results indicated high reliability in residential, industrial, and outdoor environments. The predictive analysis module effectively identified potential fire risks based on historical sensor trends. Overall, the system provided efficient, accurate, and cost-effective fire monitoring capabilities.

CONCLUSION

The AI Based Fire Detection and Prediction System provides an intelligent solution for enhancing fire safety through the integration of Artificial Intelligence, IoT, and multi-sensor technologies. The system continuously monitors environmental conditions using various sensors and a camera module. AI-based analysis and sensor fusion techniques significantly improve detection accuracy while reducing false alarms. Real-time monitoring and instant alert generation enable quick emergency response and minimize potential damage. The implementation of CNN models enhances fire and smoke recognition capabilities. IoT communication allows remote monitoring and efficient information sharing. The system operates with low power consumption and supports scalable deployment across multiple locations. Predictive analytics further strengthen fire prevention strategies by identifying risks before incidents occur. The proposed solution is cost-effective, reliable, and suitable for residential, industrial, forest, and smart city applications. Overall, the system contributes significantly to improving public safety and disaster management.

FUTURE SCOPE

The future scope of this project includes the integration of advanced deep learning models for improved fire prediction accuracy. Additional sensors such as thermal cameras and infrared sensors can be incorporated to enhance detection capabilities. Cloud-based analytics can be used for large-scale data storage and intelligent processing. Federated learning techniques may enable continuous model improvement while preserving data privacy. Automated fire suppression mechanisms can be integrated to initiate immediate firefighting actions. Drone-based monitoring systems can support surveillance in forests and remote locations. Mobile applications with enhanced user interfaces can provide better accessibility and control. Smart city integration can facilitate centralized monitoring of multiple locations. Edge AI optimization can further reduce latency and power consumption. Future developments will focus on creating a fully autonomous, highly reliable, and intelligent fire safety ecosystem capable of preventing disasters and protecting lives and property.

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