

AN AI-DRIVEN CLOUD-BASED SMART SURVEILLANCE SYSTEM FOR FIRE AND SMOKE DETECTION

T. Anusha^{1*}, E. Sneha², D. Anirudh³, B. Gopi Kiran⁴, E. Srivallab⁵

¹Assistant Professor, Department of CSE (DS), TKR College of Engineering and Technology, Meerpet, Telangana 500097

^{2,3,4,5}B.Tech (Scholars), Department of CSE (DS), TKR College of Engineering and Technology, Meerpet, Telangana 500097

*Correspondence: anushathirumani@tkrcet.com

Abstract— Fire incidents in residential, commercial, and industrial environments pose a serious threat to human life and infrastructure. Conventional fire detection systems rely mainly on smoke or temperature sensors, which often result in delayed responses and increased damage. To overcome these limitations, this research presents a **Smart Fire Surveillance System that integrates Artificial Intelligence (AI) with cloud technology for intelligent fire monitoring**.

The proposed system utilizes surveillance cameras to continuously capture video streams and applies AI-based computer vision techniques to identify fire and smoke patterns in real time. Once a fire event is detected, the system transmits the detection results to a cloud platform where the information is securely stored and analyzed. The cloud infrastructure enables remote monitoring, centralized data management, and instant notifications to users through web or mobile applications.

By combining AI-based visual detection with scalable cloud services, the system provides faster detection, minimizes false alarms, and improves response time. This solution is suitable for deployment in smart cities, industries, commercial buildings, and residential areas, offering an efficient and cost-effective approach to fire safety management.

Keywords: Fire Detection, Artificial Intelligence, Cloud Computing, Smart Surveillance, Computer Vision, IoT Monitoring.

1. INTRODUCTION

Fire hazards are one of the most dangerous emergencies that can occur in residential, commercial, and industrial environments. Every year, many fire incidents lead to severe loss of life and property [1]. Traditional fire detection systems such as smoke

detectors and temperature sensors play an important role in fire safety, but they often detect fire only after it reaches a critical level. These systems also face challenges such as delayed detection, environmental interference, and limited monitoring capabilities [2].

With the rapid development of modern technologies such as Artificial Intelligence, Internet of Things, and Cloud Computing, new intelligent systems have been developed to improve fire detection and monitoring [3-5]. Artificial Intelligence, particularly computer vision techniques, allows machines to analyze visual data and recognize specific patterns within images and videos [6]. This capability makes it possible to detect flames and smoke directly from surveillance camera feeds.

The Smart Fire Surveillance System using AI and Cloud is designed to provide an advanced fire detection solution by combining real-time monitoring, deep learning algorithms, and cloud-based data management [7]. In this system, cameras continuously capture images and videos from the monitored area. These images are processed using deep learning models that can identify fire or smoke characteristics [8-9]. When a fire event is detected, the system immediately sends alerts and stores the event information in a cloud platform for monitoring and analysis.

The use of cloud technology enables centralized data storage and remote accessibility [10-12]. Users can monitor fire detection events from anywhere through a dashboard interface. The cloud platform also allows historical data analysis, which helps in improving system performance and understanding fire patterns [13].

To achieve accurate detection, the system uses advanced deep learning models such as Convolutional

Neural Networks and YOLO object detection algorithms [14]. These models are trained using datasets containing fire and non-fire images [15]. By analyzing visual features such as flame color, movement, and smoke patterns, the models can identify fire hazards quickly and efficiently [16].

The proposed system consists of several modules including Data Acquisition, Image Processing, AI-based Detection, Cloud Data Management, Monitoring Dashboard, and Alert Notification System. Each module works together to ensure efficient fire detection and monitoring. The system provides several advantages such as early detection, reduced false alarms, real-time monitoring, and remote accessibility.

2. LITERATURE SURVEY

Fire detection has been an important research area in the field of safety monitoring and disaster prevention [17]. Traditional fire detection systems mainly rely on smoke detectors, heat sensors, and gas sensors to identify fire hazards [18-19]. Although these systems are widely used, they often detect fire only after significant environmental changes occur, which may lead to delayed responses and increased damage. In addition, environmental conditions such as dust, steam, and temperature fluctuations can produce false alarms [20]. Because of these limitations, researchers have focused on developing intelligent fire detection systems using computer vision and artificial intelligence techniques.

With the advancement of deep learning technologies, many researchers have proposed visual fire detection systems that analyze images and video streams [21]. These systems use computer vision algorithms to identify fire and smoke patterns directly from surveillance cameras [22]. Deep learning models such as Convolutional Neural Networks (CNN) have been widely used for image classification and pattern recognition tasks [23]. CNN models can automatically extract important visual features such as color, texture, and shape from images, making them highly effective for detecting flames and smoke in surveillance footage [24]. Research studies have shown that CNN-based models significantly improve fire detection accuracy compared to traditional machine learning methods.

Recent studies have also explored object detection algorithms for real-time fire monitoring [25]. One of the most widely used approaches is the YOLO (You Only Look Once) object detection model. YOLO is capable of detecting objects in images and videos in a single step, making it suitable for real-time applications [26]. Researchers have applied YOLO-based models to identify fire and smoke regions in surveillance video streams. These models are trained using labeled datasets containing fire and non-fire images, allowing them to recognize fire patterns with high accuracy and speed. Studies show that YOLO-based fire detection systems can provide fast and reliable detection with minimal processing delay.

In addition to CNN and YOLO models, researchers have also investigated improved deep learning architectures for fire detection. Some studies propose lightweight models and attention-based networks that enhance feature extraction and improve detection accuracy in complex environments [27]. These models are designed to handle challenges such as small fire targets, occlusion, and background interference [28]. Recent research has shown that modified YOLO architectures and attention mechanisms can significantly improve fire detection performance while maintaining real-time processing capability.

Furthermore, many modern fire detection systems integrate cloud computing technology for efficient data storage and remote monitoring. Cloud platforms allow large volumes of surveillance data to be stored and analyzed centrally [29]. They also enable users to monitor multiple locations through web-based dashboards and receive real-time alerts when fire is detected. The integration of artificial intelligence with cloud infrastructure has improved scalability, accessibility, and reliability in fire surveillance systems.

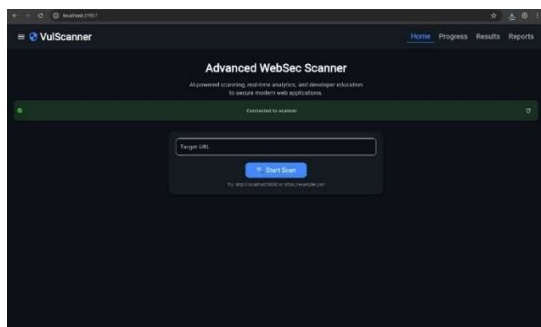
Based on these research advancements, it is clear that combining deep learning models with cloud-based monitoring systems provides a promising approach for early fire detection [30]. The Smart Fire Surveillance System using AI and Cloud builds upon these existing technologies by integrating real-time video analysis, deep learning-based fire detection, and cloud-based

data management to provide an efficient and reliable fire monitoring solution.

3. PROPOSED METHODOLOGY

1. Data Acquisition and Input Interface

The proposed system provides a user-friendly web interface that allows users to monitor camera feeds, upload images, and manage fire surveillance data. The interface is developed using modern web technologies to ensure fast performance and easy accessibility across different devices. The system collects input data from CCTV cameras, webcams, and manual image uploads. Real-time video streams are captured and converted into frames using computer vision techniques. These frames act as the primary input for the fire detection model. The interface also allows administrators to monitor system status and view detection results in real time.



2. Image Preprocessing and Frame Extraction

Before processing the captured data, image preprocessing techniques are applied to improve the quality and reliability of the input. Each frame extracted from the video stream is resized and normalized to match the input requirements of the deep learning model. Noise reduction and low-light enhancement techniques are also applied to handle challenging environmental conditions. These preprocessing steps help remove unnecessary distortions and ensure that the AI model receives clean and standardized input data for accurate fire detection.

3. AI-Based Fire Detection Model

The core component of the proposed system is an AI-based fire detection engine built using deep learning techniques. A Convolutional Neural Network (CNN) is trained using fire and non-fire image datasets to learn visual patterns associated with flames and

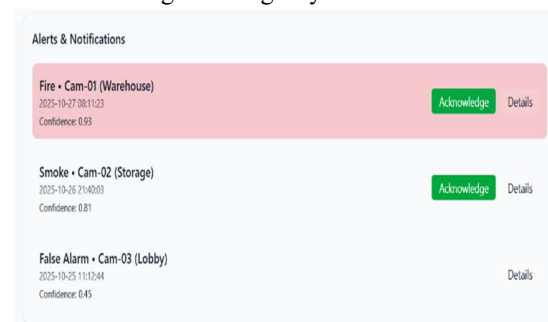
smoke. The trained model analyzes each preprocessed frame and predicts whether fire is present. The prediction is accompanied by a confidence score that indicates the probability of fire detection. This AI-based approach allows the system to automatically detect fire in real time with high accuracy and minimal human intervention.

4. Cloud Data Storage and Event Logging

To ensure scalability and secure data management, the system integrates cloud services for storing detection results and event logs. When fire is detected, the corresponding frame is uploaded to cloud storage for future analysis and evidence. Detection details such as timestamp, detection status, and image path are recorded in a cloud database. Cloud integration enables centralized monitoring, efficient data retrieval, and reliable storage of surveillance data without overloading local system resources.

5. Alert and Notification Mechanism

Once the AI model confirms the presence of fire, the system immediately triggers an alert mechanism. Notifications are sent to authorized users through email, SMS, or push notifications using cloud-based messaging services. This ensures that responsible personnel are informed instantly about potential fire incidents. The alert module also logs each notification event in the system database, enabling proper tracking and monitoring of emergency alerts.



6. Monitoring and Dashboard System

A centralized dashboard is developed to provide real-time monitoring and visualization of the fire surveillance system. The dashboard displays live camera feeds, fire detection results, sensor data, and alert notifications. Administrators can view system status, monitor ongoing incidents, and access historical detection logs. The dashboard also provides

visual indicators such as detection confidence scores and event timestamps, allowing users to quickly assess the severity of a fire event.

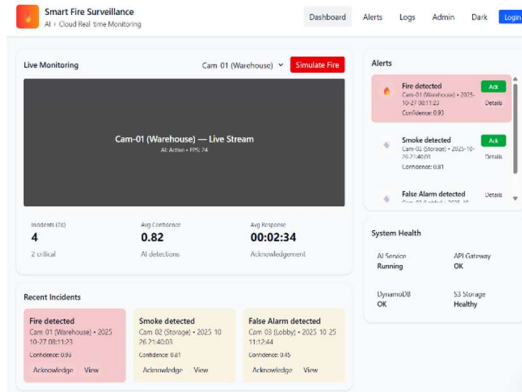


Fig..3. Report Export Format

4. ARCHITECTURE

The model architecture detects fire in real time using surveillance cameras, AI models, and cloud monitoring. The system analyzes visual data, stores results in the cloud, and sends alerts for quick response.

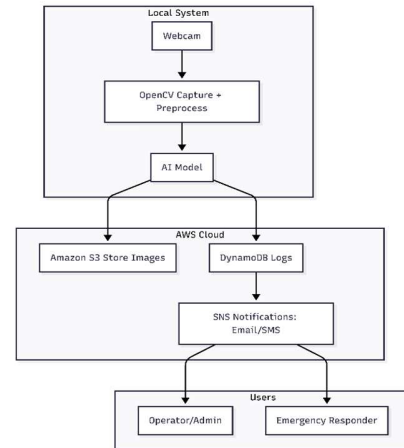
a) Surveillance Camera Layer

The first component of the architecture is the **surveillance camera layer**, which is responsible for capturing visual data from the monitored environment. Cameras installed in different locations continuously record live video streams of the surroundings. These cameras act as the primary data source for the system. The captured video streams are transmitted to the processing unit where they are further analyzed. High-resolution cameras are typically used to ensure that fire and smoke patterns can be clearly detected by the system.

b) Data Processing and Preprocessing Layer

Once the video data is captured, it enters the **data processing and preprocessing layer**. In this stage, the video streams are converted into individual image frames so that each frame can be analyzed independently. Image preprocessing techniques such as resizing, noise removal, brightness adjustment, and contrast enhancement are applied to improve the quality of the captured frames. These preprocessing

operations help highlight important features and remove distortions, making the images suitable for accurate fire detection by the AI model.



c) AI Fire Detection Layer

Once preprocessing is completed, the processed frames are analyzed using artificial intelligence models. Deep learning techniques such as **Convolutional Neural Networks (CNN)** and object detection models like **YOLO (You Only Look Once)** are used to detect fire and smoke patterns within the images. These models analyze important visual characteristics including flame color, smoke movement, brightness levels, and shape patterns. If the model identifies a potential fire with a confidence score above a predefined threshold, the system classifies the event as a fire incident.

d) Cloud Data Management Layer

After fire detection, the results are transmitted to a cloud platform where all relevant data is stored and managed. The cloud infrastructure stores information such as captured images, detection timestamps, event status, and system logs. Cloud technology ensures that the system data is scalable, secure, and accessible from remote locations. It also allows the system to maintain historical records of fire incidents, which can be useful for future analysis and system improvement.

e) Monitoring Dashboard Layer

The stored data is then displayed through a monitoring dashboard that provides a user-friendly interface for administrators and monitoring authorities. The

dashboard enables users to observe real-time detection results, view live camera feeds, and analyze historical fire detection data. This centralized monitoring system allows users to manage multiple surveillance locations and respond quickly when a fire event occurs.

f) Alert and Notification Layer

The final component of the architecture is the **alert and notification layer**, which ensures that users are immediately informed when a fire event is detected. Once the AI model confirms a fire incident, the system automatically generates alerts and sends notifications through communication channels

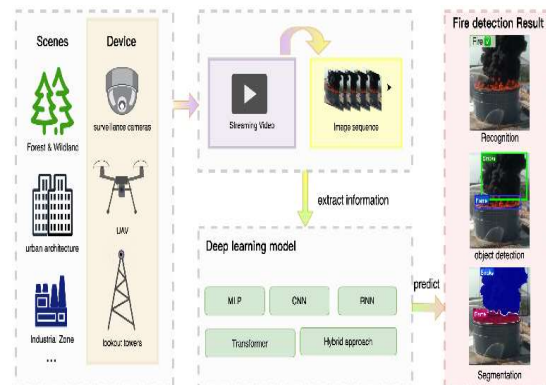
such as email, SMS, or mobile application notifications. These alerts include important details such as the location of the fire, the detection time, and visual evidence captured by the cameras. This rapid notification mechanism enables quick response and helps reduce the damage caused by fire incidents.

5. RESULT

The Smart Fire Surveillance System was successfully developed and tested to monitor fire incidents in real time using artificial intelligence and cloud technologies. The system captures live video streams from cameras, processes the frames using an AI-based fire detection model, and triggers alerts when fire is detected. The experimental results demonstrate that the proposed system can accurately identify fire patterns and provide timely alerts to users.

The data acquisition module effectively collected real-time video streams and image inputs from surveillance cameras. The preprocessing stage improved image quality by resizing frames, removing noise, and normalizing pixel values. These preprocessing steps ensured that the AI model received clean and structured input data for accurate fire detection.

The AI-based fire detection engine analyzed each video frame and classified it as **Fire** or **No Fire** using the trained convolutional neural network model. The system generated a confidence score for each prediction, which helped determine the reliability of the detection result. The model successfully detected fire in various testing scenarios including indoor fire simulations and recorded fire footage.



The cloud data management module stored detection results and captured images securely in the cloud database. Each fire detection event was logged with details such as timestamp, detection status, and image path. This allowed the system to maintain a structured history of fire incidents for future analysis and monitoring. The monitoring dashboard provides a centralized interface for administrators to observe fire surveillance activities in real time. The dashboard displays live camera feeds, fire detection results, event logs, and system alerts. When the AI model detects fire, the dashboard highlights the detection result along with a

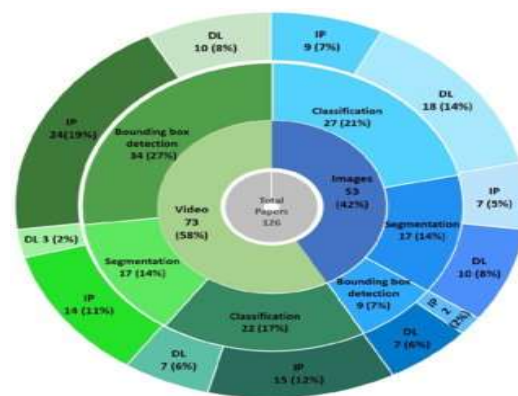


Fig.5.1. AI scan progress score



To analyze the performance of the system, fire detection events were recorded over a specific monitoring period. The data was visualized using line graphs to understand how fire incidents changed over time. The graph shows the number of fire detections observed during different time intervals. The analysis indicates that the system consistently detects fire events and maintains stable monitoring performance. Such visualization helps in identifying fire-prone time periods and improving safety planning. The overall performance of the AI model was evaluated using classification results obtained during testing. The detection outcomes were categorized into fire detections, non-fire detections, and uncertain predictions. The pie chart illustrates the distribution of detection results across these categories. The experimental results demonstrate that the AI model achieved high accuracy in identifying fire events while minimizing false detections.

6. CONCLUSION & FUTURE SCOPE

The **Smart Fire Surveillance System using AI and Cloud** provides an efficient and intelligent solution for early fire detection and real-time monitoring. By integrating surveillance cameras, artificial intelligence algorithms, and cloud technology, the system can continuously monitor environments and analyze visual data to identify fire and smoke patterns accurately. The AI models enable quick detection of fire incidents, while the cloud platform ensures secure storage,

Incident tracking dashboard for facilitating trend analysis



centralized monitoring, and remote access to surveillance data. The system also generates instant alerts through dashboards or notifications, allowing users and authorities to respond quickly and reduce potential damage. Overall, the proposed system improves fire safety by providing faster detection, better monitoring, and more reliable data management compared to traditional fire detection methods. In the future, the system can be further enhanced by integrating advanced deep learning models to improve detection accuracy in complex environments. The addition of Internet of Things (IoT) sensors such as smoke, gas, and temperature detectors can provide multi-layer fire detection and increase reliability. The development of mobile applications can allow users to monitor the system remotely and receive real-time alerts. Furthermore, technologies such as drone-based surveillance, edge computing, and integration with smart city infrastructure can expand monitoring coverage and improve emergency response. These improvements will make the Smart Fire Surveillance System more scalable, intelligent, and effective for large-scale fire safety management.

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