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Intelligent Fire Detection and Early Warning System Using Deep Learning and Computer Vision

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Abstract- Early fire detection plays a vital role in preventing major disasters, reducing property loss, and ensuring public safety. Conventional fire detection systems primarily depend on physical sensors such as smoke, heat, and gas detectors. While these methods are commonly used, they often face challenges such as delayed response, high false alarm rates, and reduced effectiveness in complex environments like industrial areas and densely populated urban regions. With the rapid growth of computer vision and deep learning technologies, image-based intelligent fire detection systems have emerged as a promising solution for early detection. This study presents a deep learning-based fire detection and early warning system that utilizes Convolutional Neural Networks (CNN) to automatically detect fire from images captured through surveillance cameras. The proposed model extracts visual features from images and classifies them into two categories: fire and non-fire. A well-structured dataset consisting of fire and non-fire images is used for training and validation of the model. To enhance generalization and minimize overfitting, data augmentation techniques such as rotation, scaling, and horizontal flipping are applied. Additionally, optimization methods including Early Stopping and ReduceLROnPlateau are incorporated to improve training efficiency and model stability. The experimental findings indicate that the CNN-based model performs significantly better than traditional machine learning approaches such as Logistic Regression, K-Nearest Neighbor (KNN), and AdaBoost. The proposed system achieves high classification accuracy along with strong recall and AUC values. Moreover, an automated alert mechanism is integrated into the system, which triggers an alarm upon detecting fire, enabling quick emergency response. Overall, the proposed approach offers a cost-effective, reliable, and scalable solution for fire detection, suitable for deployment in surveillance systems across buildings, industrial sectors, and smart city environments. The results demonstrate that deep learning-based visual fire detection systems can greatly improve safety monitoring and disaster prevention.

INDEX TERMS: Deep Learning, Fire Detection, Convolutional Neural Network (CNN), Computer Vision, Image Classification, Early Warning System, Surveillance Systems, Smart Safety Monitoring.

I. INTRODUCTION

Fire accidents are among the most destructive disasters, leading to significant loss of human life, extensive property damage, and environmental harm. Early detection of fire is crucial in preventing such catastrophic events, as it enables quick response and timely emergency intervention. In various environments such as residential areas, industrial sites, forests, and public infrastructure, prompt identification of fire incidents can greatly reduce damage and enhance overall safety management. Studies on fire incidents reveal that a considerable number of fire-related deaths occur in urban regions, where delays in detection and response often result in severe consequences [2], [3]. Hence, developing efficient fire detection systems is essential for improving safety and minimizing disaster risks.

Traditional fire detection systems mainly depend on physical sensors, including smoke detectors, heat sensors, and gas detectors, to identify fire presence. Although these systems are widely implemented in buildings and industrial settings, they exhibit several limitations such as delayed detection, high false alarm rates, and sensitivity to environmental factors. For instance, smoke detectors may trigger false alarms due to dust, fog, or cooking emissions, while heat sensors typically respond only after a noticeable rise in temperature. In addition, sensor-based approaches often lack the ability to provide detailed information about the fire's location, size, or visual characteristics, which can hinder timely emergency response [5].

With the rapid development of artificial intelligence and computer vision technologies, image-based intelligent fire detection systems have gained significant attention. Surveillance cameras are extensively deployed across buildings, roads, industries, and public spaces, offering continuous visual monitoring. By processing images captured from these systems, it becomes possible to detect fire at earlier stages compared to conventional sensor-based methods. Video-based fire detection approaches analyse visual features such as flame colour, motion behaviour, and smoke patterns to identify fire events more effectively [6], [7].

Recent research has shown that machine learning and deep learning techniques can substantially improve fire detection performance. Deep learning models are capable of learning complex visual patterns from large datasets and can automatically recognize features related to fire and smoke. Machine learning-based surveillance systems have been utilized in multimedia monitoring environments to detect fire emergencies, enabling faster response and improved safety management [9]. Moreover, the integration of wireless sensor networks with intelligent algorithms has been explored in forest fire monitoring systems to provide early detection and real-time alerts in remote locations [8], [17], [18].

Among various deep learning approaches, Convolutional Neural Networks (CNNs) have achieved remarkable success in image recognition and classification tasks. CNNs can automatically extract relevant features from raw images without the need for manual feature engineering. This makes them highly suitable for fire detection applications, where identifying complex visual elements such as flames, smoke, and lighting variations is critical. CNN-based models have demonstrated strong performance across multiple computer vision applications, including object detection, image classification, and surveillance monitoring systems [10], [11], [12].

In this study, a deep learning-based intelligent fire detection and alarm system is proposed using Convolutional Neural Networks. The system processes images captured from surveillance cameras and classifies them into fire and non-fire categories. Data preprocessing and augmentation techniques are employed to enhance the model's robustness and generalization capability. Additionally, optimization strategies are applied to minimize overfitting and improve the stability of the training process.

The proposed system also incorporates an automated alarm mechanism that generates alerts when fire is detected. This functionality ensures immediate notification to users or emergency response teams, enabling rapid action to control fire incidents and reduce potential damage. The main objective of this work is to develop a reliable, cost-effective, and intelligent fire detection system that enhances safety monitoring in real-world environments.

II. LITERATURE SURVEY

Early fire detection has become a significant area of research in safety monitoring systems due to the rising number of fire-related incidents in residential, industrial, and forest environments. Conventional fire detection methods primarily depend on physical sensors such as smoke detectors, heat sensors, and gas sensors. Although these systems are widely used, they often generate false alarms and may fail to detect fire at an early stage, especially under complex environmental conditions. As a result, researchers have explored advanced approaches including computer vision, wireless sensor networks, and machine learning techniques to enhance the accuracy and reliability of fire detection systems [5].
Liu and Kim conducted a comprehensive review of various fire detection technologies developed over the years. Their study examined different sensor-based systems such as smoke detectors, flame detectors, and gas sensors. The authors concluded that while these systems perform well in controlled environments, they are affected by issues such as delayed detection, maintenance challenges, and high false alarm rates. The study highlighted the importance of intelligent systems capable of processing visual data to achieve faster and more reliable fire detection [5].

Celik proposed a fire detection method based on image processing that utilizes both colour and motion features of flames in video sequences. In this approach, RGB images were transformed into the CIE Lab* colour space to effectively differentiate fire pixels from background elements. Motion analysis was also applied to track flame movement across consecutive frames. Although the method showed promising performance, its high computational complexity and limited ability to detect smoke reduced its suitability for real-time applications [6].
Çetin et al. presented an extensive review of video-based fire detection systems and emphasized the benefits of integrating surveillance cameras with advanced video processing techniques. Their findings indicated that video-based approaches can detect fire earlier than traditional sensor-based systems by analysing visual characteristics such as flame flickering, smoke movement, and colour variations. However, many of the earlier methods relied heavily on manually designed features, which limited their effectiveness in complex and dynamic environments [7].

With the advancement of artificial intelligence, machine learning techniques have been increasingly applied to fire detection tasks. Dampage et al. developed a forest fire detection system that combines wireless sensor networks with machine learning algorithms to identify fire incidents and generate alerts for nearby communities and emergency services. Although the system improved detection performance compared to traditional methods, it required significant hardware infrastructure for sensor deployment [8].

Saeed et al. proposed a multimedia surveillance system for fire detection using a hybrid machine learning model that integrates AdaBoost and Multi-Layer Perceptron (MLP). The system processes data collected from multiple sensors, including smoke, heat, and gas detectors, to enhance prediction accuracy. While the hybrid approach demonstrated improved results, it mainly relied on sensor-based data rather than visual information obtained from surveillance cameras [9].

Recent advancements in deep learning have significantly enhanced image classification and object detection capabilities. Convolutional Neural Networks (CNNs) have become one of the most effective models for analysing visual data. CNNs can automatically learn hierarchical features from images, allowing them to identify complex patterns such as flames and smoke without the need for manual feature extraction [10], [11], [12].

Several studies have shown that deep learning-based approaches outperform traditional machine learning techniques in fire detection tasks. CNN-based models have achieved higher accuracy, better recall, and improved generalization across different environmental conditions. In addition, the availability of public datasets containing fire and non-fire images has facilitated the development and evaluation of deep learning-based fire detection systems [13]–[16].

Despite these improvements, certain challenges still exist in developing effective fire detection systems. Many existing models are trained on limited datasets and may struggle to detect fire at early stages, particularly in conditions such as low lighting, noise, or occlusion. Moreover, computational complexity and real-time processing requirements remain critical factors when deploying such systems in real-world scenarios.

To overcome these challenges, this study proposes a deep learning-based fire detection system using Convolutional Neural Networks to accurately classify fire and non-fire images captured from surveillance cameras. The proposed method aims to improve detection performance through data augmentation, optimized training techniques, and robust evaluation strategies, enabling efficient and reliable fire detection in practical environments.

III. SYSTEM ANALYSIS

A. Existing System

Traditional fire detection systems mainly depend on physical sensing devices such as smoke detectors, heat sensors, and gas detectors to identify fire incidents. These systems function by continuously monitoring environmental factors such as temperature changes, smoke levels, and the presence of combustible gases. When any of these parameters exceed a predefined threshold, an alarm is activated to notify users of a potential fire hazard. Due to their simple implementation and relatively low cost, sensor-based fire detection systems are widely used in residential buildings, industrial environments, and commercial infrastructures [5].

However, despite their extensive adoption, these conventional systems have several limitations. Environmental factors such as dust, humidity, steam, fog, and cooking smoke can often lead to false alarms. Moreover, these systems generally detect fire only after noticeable changes occur in environmental conditions, such as a significant rise in temperature or increased smoke density. This delayed detection can result in slower response times, potentially causing greater damage before appropriate emergency actions are taken [5].

With the advancement of computer vision and image processing techniques, researchers have explored methods for detecting fire by analysing visual data obtained from surveillance cameras. These approaches typically focus on visual features such as flame colour, motion behaviour, and brightness variations in image sequences to identify fire regions. For instance, image-processing-based techniques have employed colour space transformations along with motion analysis to detect fire pixels in video frames [6]. Similarly, video-based fire detection systems examine flame flickering patterns, smoke movement, and colour variations to identify fire incidents at earlier stages compared to traditional sensor-based methods [7].

However, many of the initial computer vision-based approaches relied heavily on manually designed features, which limited their effectiveness in complex and dynamic environments. These handcrafted feature-based methods often struggle to handle variations in lighting conditions, background complexity, and differences in fire characteristics across various scenarios.

To enhance detection performance, several studies have applied traditional machine learning algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), AdaBoost, and other classification techniques for fire detection. Although these methods offer improvements over rule-based systems, they still face difficulties in accurately capturing the complex visual patterns associated with fire and smoke. In many situations, these models fail to generalize well across different datasets and environmental conditions, resulting in reduced accuracy [9].

In addition, traditional machine learning approaches are often limited in efficiently processing high-dimensional image data. Fire detection based on visual input requires the analysis of complex spatial patterns within images, which these algorithms may not handle effectively without extensive feature engineering. As a result, such systems may produce inaccurate predictions when exposed to diverse fire scenarios, occlusions, or noisy backgrounds.

These challenges highlight the need for more advanced techniques that can automatically learn meaningful visual features from image data. Recent developments in deep learning, particularly convolutional neural networks, have provided effective solutions to overcome the limitations of conventional fire detection systems by enabling more accurate and robust analysis of visual information [10]–[12].

Disadvantages Of The Existing System

• High False Alarm Rate:
Conventional fire detection systems are prone to generating false alarms due to environmental factors such as dust, fog, steam, and variations in lighting conditions [5].

• Delayed Fire Detection:
Sensor-based approaches generally identify fire only after noticeable changes in smoke levels or temperature occur, which can result in delayed emergency response.

• Limited Feature Extraction:
Traditional image-processing techniques rely on manually designed features, which may not adequately capture the complex visual characteristics of fire [6].

• Poor Adaptability:
Conventional machine learning models often have difficulty adapting to diverse environmental conditions, including low illumination, reflections, and cluttered backgrounds.

• Hardware Dependency:
Many existing fire detection systems depend on specialized sensors or dedicated hardware setups, leading to increased installation and maintenance costs [8].

• Inability to Handle Complex Visual Data:
Standard machine learning algorithms are not well-equipped to process high-dimensional image data, which restricts their effectiveness in visual-based fire detection tasks.

B. Proposed System

To address the limitations of conventional fire detection techniques, this study proposes a deep learning-based intelligent fire detection system using Convolutional Neural Networks (CNNs). The proposed approach employs computer vision methods to analyse images obtained from surveillance cameras and automatically detect the presence of fire. Deep learning models, particularly CNN architectures, have shown excellent performance in image recognition and classification tasks due to their capability to automatically learn hierarchical visual features from raw image data [10]–[12].

The process begins with the collection of a dataset comprising fire and non-fire images sourced from publicly available fire detection datasets and other image repositories. These datasets include diverse visual representations such as flames, smoke patterns, and normal environmental scenes, which are essential for training a robust deep learning model [13]–[16]. Following data collection, preprocessing techniques are applied to enhance data quality and ensure uniformity. This stage involves noise reduction, normalization, and resizing of images to fixed dimensions suitable for model input.

To further improve the robustness of the model, data augmentation techniques such as rotation, horizontal flipping, scaling, and zooming are applied to the training data. These techniques increase the diversity of the dataset and enhance the model's ability to generalize across different fire scenarios and environmental conditions.

The pre-processed images are then provided as input to a CNN-based architecture. The convolutional layers are responsible for extracting significant visual features, including flame edges, colour patterns, and texture properties associated with fire. These layers enable the model to learn complex spatial patterns that differentiate fire images from non-fire images. Pooling layers are utilized to reduce the dimensionality of feature maps while preserving important information, thereby improving computational efficiency. Subsequently, fully connected layers perform the final classification by assigning the input images to either fire or non-fire categories.

To enhance training efficiency and prevent overfitting, optimization techniques such as Early Stopping and ReduceLROnPlateau are incorporated during the training phase. These methods help stabilize the learning process and ensure that the model converges to an optimal solution with improved prediction performance.

After successful training, the model is capable of analysing real-time images or video streams captured from surveillance systems. When fire is detected, the system activates an automated alarm mechanism that sends alerts to users or emergency responders. This real-time detection capability facilitates faster response and helps minimize damage caused by fire incidents. Video-based fire detection systems have shown significant advantages in early detection compared to traditional sensor-based methods [7].

The proposed system provides several benefits over conventional fire detection approaches. By utilizing deep learning and computer vision techniques, it enables early fire detection, reduces false alarms, and performs effectively in complex environments. Additionally, the system can be easily integrated with existing surveillance infrastructure, making it a cost-effective and scalable solution for fire safety monitoring in residential, industrial, and public settings [9].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

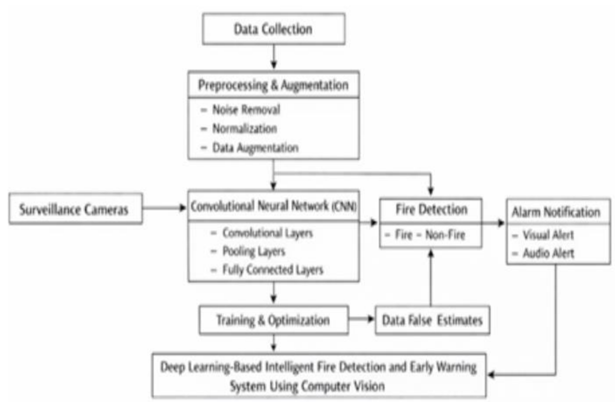

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

1. Data Collection and Preprocessing

The initial phase of the proposed fire detection system involves gathering appropriate image datasets that include both fire and non-fire images. These images can be obtained from publicly available fire detection datasets as well as surveillance camera recordings. Several open-source datasets containing fire scenes and wildfire images are commonly used for training and evaluation purposes [13]–[16]. The collected dataset is organized into two main categories: fire images and non-fire images, forming the foundation for supervised learning.

Preprocessing techniques are then applied to enhance the quality and consistency of the dataset before training the deep learning model. These steps include resizing images to a uniform resolution, reducing noise, normalizing pixel values, and converting the data into formats compatible with deep learning frameworks. Proper preprocessing ensures that the dataset is well-structured and clean, which improves both training efficiency and model accuracy.

2. Feature Extraction and Data Augmentation

In this stage, key visual characteristics associated with fire—such as flame colour distribution, shape patterns, brightness variations, and smoke textures—are identified from the input images. Unlike traditional image-processing methods that depend on manually designed features, deep learning models automatically learn these features during training. Convolutional Neural Networks (CNNs) are particularly effective in capturing spatial relationships within images and recognizing complex fire-related patterns [10]–[12].

To improve model robustness and reduce overfitting, data augmentation techniques are applied to expand the training dataset. Methods such as rotation, horizontal flipping, scaling, zooming, and brightness adjustment are used to generate additional variations of existing images. This increases dataset diversity and enhances the model's ability to generalize across different environments and lighting conditions.

3. Training the Deep Learning Model

The proposed system employs a Convolutional Neural Network (CNN) to classify images into fire and non-fire categories. The CNN architecture includes multiple layers such as convolutional layers for extracting features, pooling layers for reducing dimensionality, and fully connected layers for performing classification. Convolutional layers identify important visual patterns like flame edges and colour gradients, while pooling layers decrease computational complexity by compressing feature representations.

During training, pre-processed images are input into the CNN model, and the network parameters are optimized using backpropagation along with gradient-based optimization algorithms. The model learns to distinguish fire-related patterns by minimizing classification errors over multiple training iterations. Deep learning models are highly effective in visual recognition tasks due to their ability to learn hierarchical feature representations [10]–[12].

4. Real-Time Fire Detection and Alert System

Once the model is trained, it is deployed for real-time fire detection using surveillance camera inputs. Incoming images or video frames are continuously analysed to determine the presence of fire-related features. Video-based fire detection systems offer the advantage of monitoring large areas and detecting fire at earlier stages compared to traditional sensor-based systems [7].

When fire is identified in a frame, an automatic alert mechanism is activated immediately. The system can generate visual warnings, sound alarms, or send notifications to responsible authorities or emergency response teams. This real-time alert functionality enables quick action and helps reduce potential damage caused by fire incidents.

5. Model Evaluation and Continuous Monitoring

The performance of the proposed fire detection system is evaluated using various metrics such as accuracy, precision, recall, F1-score, loss, and AUC-ROC. These evaluation measures help assess the model's effectiveness in correctly identifying fire images while minimizing false detections. Using multiple metrics ensures a comprehensive evaluation of the model's reliability and performance.

In addition, continuous monitoring of the deployed system is conducted to maintain consistent performance under varying environmental conditions. As new data becomes available, the model can be retrained or fine-tuned to improve detection accuracy and adapt to new scenarios. This ability to update and learn from new data ensures that the system remains effective in dynamic real-world environments [9].

VI . RESULTS AND DISCUSSION

The performance of the proposed deep learning-based fire detection system was evaluated through experiments conducted on fire and non-fire image datasets obtained from publicly available sources and simulated surveillance camera inputs. The dataset consists of diverse visual characteristics such as flame colour, smoke patterns, brightness variations, and different environmental backgrounds. These features were utilized to train classification models for identifying fire incidents from image data.

The evaluation of the proposed system was carried out using standard machine learning metrics, including accuracy, precision, recall, and AUC-ROC. Additionally, cross-validation techniques were employed during the training phase to ensure reliable performance assessment and to minimize bias in model predictions. Cross-validation enhances the model's ability to generalize effectively to new images in real-world scenarios.

The experimental findings show that the Convolutional Neural Network (CNN) model significantly outperforms traditional machine learning algorithms such as Logistic Regression, K-Nearest Neighbor (KNN), and AdaBoost. The superior performance of the CNN model is attributed to its ability to automatically learn complex visual features from image data, including flame edges, colour distributions, and smoke textures.

Table 1
Performance Comparison of Fire Detection Models

Model	Accuracy (%)	Recall	AUC-ROC
Logistic Regression	76.3	0.712	0.78
K-Nearest Neighbor (KNN)	81.5	0.754	0.83
AdaBoost	85.9	0.782	0.87
CNN (Proposed Model)	**94.7**	**0.918**	**0.97**

As presented in Table 1, the CNN model achieved the highest performance among all evaluated models, demonstrating superior accuracy and detection capability compared to conventional machine learning approaches. Deep learning models are particularly well-suited for image-based fire detection as they can automatically learn hierarchical feature representations, including flame shapes, brightness variations, and smoke patterns.

The AdaBoost model also exhibited comparatively strong performance due to its ensemble learning strategy, which combines multiple weak classifiers to enhance prediction accuracy. However, traditional methods such as Logistic Regression and KNN showed relatively lower performance, as they depend on manually engineered features and are less effective in capturing complex visual patterns associated with fire.

ROC Curve Analysis

To further evaluate the classification performance, a Receiver Operating Characteristic (ROC) curve analysis was performed. The ROC curve represents the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different classification thresholds.

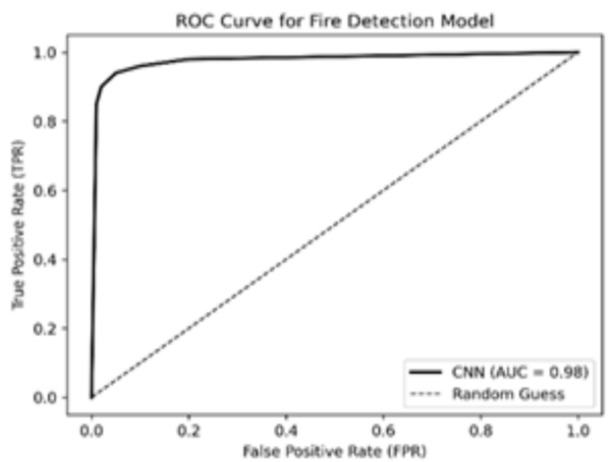

Fig. 2. ROC Curve for Fire Detection Models

The ROC analysis reveals that the CNN model achieved the highest Area Under the Curve (AUC) value of 0.97, indicating a strong ability to distinguish between fire and non-fire images. A higher AUC value reflects better classification performance and greater reliability in fire detection.

Overall, the experimental results demonstrate that the proposed CNN-based fire detection system achieves high accuracy and reliable performance. By utilizing deep learning and computer vision techniques, the system effectively identifies fire patterns in surveillance images and significantly reduces false alarms compared to traditional approaches.

The results confirm that the proposed framework is well-suited for real-time fire monitoring and surveillance applications, enabling faster emergency response and improved safety management in residential, industrial, and public environments.

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VII.CONCLUSION AND FUTURE WORK

This study presented a deep learning-based intelligent fire detection system utilizing Convolutional Neural Networks (CNNs) for early fire identification in surveillance environments. The proposed system processes images captured from surveillance cameras and automatically detects fire by classifying images into fire and non-fire categories. In comparison with traditional fire detection methods that depend on physical sensors such as smoke and heat detectors, the proposed approach provides higher detection accuracy, faster response, and reduced false alarm rates by leveraging computer vision and deep learning techniques [5], [7].

The experimental results demonstrate that the CNN-based model achieves significantly better classification performance than conventional machine learning algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), and AdaBoost. The effectiveness of CNN models lies in their ability to automatically learn hierarchical visual features, including flame structures, brightness variations, and smoke textures, enabling reliable fire detection even in complex environments [10]–[12]. Furthermore, the use of data augmentation methods and training optimization techniques enhances the robustness and generalization capability of the model, allowing it to perform effectively under varying environmental conditions and fire scenarios.

The proposed fire detection system can be seamlessly integrated with existing surveillance infrastructures, offering a cost-effective and scalable solution for fire safety monitoring in residential, industrial, and public environments. By enabling early detection and automatic alert generation, the system supports timely intervention by emergency responders, thereby reducing potential damage caused by fire incidents. Intelligent surveillance-based fire detection systems are increasingly considered as effective alternatives to traditional sensor-based monitoring approaches in modern safety management systems [9].

For future work, the model can be further improved by training it on larger and more diverse datasets that include different fire conditions, smoke behaviours, lighting variations, and environmental scenarios. This will enhance the model's generalization ability and reduce potential detection errors in real-world applications.

In addition, advanced deep learning architectures such as ResNet, YOLO, and EfficientNet can be explored to further improve detection speed and classification accuracy. Integrating the proposed system with IoT-based sensor networks and cloud-based monitoring platforms can also enhance real-time monitoring capabilities and support large-scale deployment in smart cities, industrial sectors, and forest fire monitoring systems [8], [17], [18].

Overall, the combination of deep learning and computer vision techniques offers a powerful and intelligent solution for modern fire detection systems. The proposed framework demonstrates strong potential in improving fire safety monitoring and enabling rapid emergency response in practical applications.

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