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

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Abstract- Early detection of fire is critical for preventing large-scale disasters, minimizing property damage, and ensuring public safety. Traditional fire detection systems mainly rely on physical sensors such as smoke, heat, and gas detectors. Although these methods are widely used, they often suffer from delayed detection, high false alarm rates, and limitations in complex environments such as industrial facilities and crowded urban areas. With the rapid advancement of computer vision and deep learning technologies, intelligent image-based fire detection systems have emerged as an effective alternative for improving early fire detection. This paper proposes a deep learning-based intelligent fire detection and early warning system that uses Convolutional Neural Networks (CNN) to automatically identify fire in images captured from surveillance cameras. The proposed system analyses visual features from images and classifies them into two categories: fire and non-fire. A structured dataset containing fire and non-fire images is used to train and validate the deep learning model. Data augmentation techniques such as image rotation, scaling, and horizontal flipping are applied to improve model generalization and reduce overfitting. In addition, training optimization techniques including Early Stopping and ReduceLROnPlateau are implemented to enhance model performance and stability. Experimental results demonstrate that the CNN-based model significantly outperforms traditional machine learning techniques such as Logistic Regression, K-Nearest Neighbor (KNN), and AdaBoost. The proposed model achieves high classification accuracy while maintaining strong recall and AUC performance metrics. Furthermore, the system integrates an automated alarm mechanism that generates an alert when fire is detected, enabling rapid emergency response. The proposed approach provides a cost-effective, reliable, and scalable fire detection solution that can be deployed in surveillance systems for buildings, industrial environments, and smart city infrastructures. The results indicate that deep learning-based visual fire detection systems can significantly enhance disaster prevention and safety monitoring capabilities.

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

I. INTRODUCTION

Fire accidents represent one of the most destructive disasters that can cause severe loss of life, property damage, and environmental destruction. Early fire detection plays a critical role in preventing catastrophic incidents by enabling rapid response and emergency intervention. In residential buildings, industrial facilities, forests, and public infrastructure, timely detection of fire can significantly reduce the extent of damage and improve overall safety management. Reports on fire incidents indicate that a large proportion of fire-related fatalities occur in urban areas where delayed detection and response can lead to severe consequences [2], [3]. Therefore, the development of efficient fire detection systems is essential for improving safety and reducing disaster risks.

Conventional fire detection systems primarily rely on physical sensors such as smoke detectors, heat sensors, and gas sensors to detect the presence of fire. While these systems are widely deployed in buildings and industrial environments, they often suffer from several limitations including delayed response, high false alarm rates, and sensitivity to environmental conditions. For example, smoke detectors may generate false alarms due to dust, fog, or cooking smoke, while heat sensors typically detect fire only after a significant increase in temperature has occurred. Furthermore, sensor-based systems may not provide sufficient information about the location, size, or visual characteristics of the fire, which can delay emergency response actions [5].

With the rapid advancement of artificial intelligence and computer vision technologies, intelligent fire detection systems based on image analysis have gained increasing attention. Surveillance cameras are now widely installed in buildings, streets, industries, and public areas, providing continuous visual monitoring of the environment. By analysing images captured from these surveillance systems, it becomes possible to detect fire outbreaks at an earlier stage compared to traditional sensor-based approaches. Video-based fire detection systems can analyse visual patterns such as flame colour, motion characteristics, and smoke patterns to identify fire incidents more effectively [6], [7].

Recent studies have demonstrated that machine learning and deep learning techniques can significantly enhance fire detection performance. Deep learning models are capable of learning complex visual features from large datasets and can automatically identify patterns associated with fire and smoke. Machine learning-based surveillance systems have been applied to detect fire emergencies in multimedia monitoring environments, enabling faster response and improved safety management [9]. Additionally, wireless sensor networks combined with intelligent algorithms have been used in forest fire monitoring systems to provide early detection and real-time alerts in remote areas [8], [17], [18].

Among deep learning techniques, Convolutional Neural Networks (CNNs) have shown remarkable success in image recognition and classification tasks. CNN models can automatically extract meaningful features from raw images without requiring manual feature engineering. This capability makes CNNs particularly suitable for fire detection applications, where identifying complex visual patterns such as flames, smoke, and illumination changes is essential. CNN-based models have demonstrated strong performance in various computer vision applications, including object detection, image classification, and surveillance monitoring systems [10], [11], [12].

In this research, a deep learning-based intelligent fire detection and alarm system is proposed using convolutional neural networks. The proposed system analyses images obtained from surveillance cameras and classifies them into fire and non-fire categories. Data preprocessing and augmentation techniques are applied to improve the robustness and generalization capability of the model. Furthermore, optimization techniques are used to reduce overfitting and enhance the stability of the training process.

The proposed system also integrates an automated alarm mechanism that triggers alerts when fire is detected. This feature enables immediate notification to users or emergency response teams, allowing rapid intervention to control fire incidents and minimize potential damage. The overall objective of this study is to develop a reliable, cost-effective, and intelligent fire detection system capable of improving safety monitoring in real-world environments.

The remainder of this paper is organized as follows. Section II presents a review of existing research on fire detection systems and deep learning-based monitoring techniques. Section III describes the proposed methodology and system architecture. Section IV discusses the implementation details of the model and experimental setup. Section V presents the results and performance evaluation of the proposed system. Finally, Section VI concludes the study and highlights potential directions for future work.

II. LITERATURE SURVEY

Early fire detection has been an important research area in safety monitoring systems due to the increasing number of fire-related disasters occurring in residential, industrial, and forest environments. Traditional fire detection systems mainly rely on physical sensors such as smoke detectors, heat sensors, and gas sensors. Although these systems are widely deployed, they often produce false alarms and may fail to detect fire in its early stages under complex environmental conditions. Consequently, researchers have explored advanced technologies such as computer vision, wireless sensor networks, and machine learning techniques to improve the reliability and accuracy of fire detection systems [5].

Liu and Kim presented a comprehensive review of various fire detection technologies developed over several years. Their study analysed different types of sensor-based fire detection systems including smoke detectors, flame detectors, and gas sensors. The authors reported that although these systems perform effectively in controlled environments, they often suffer from limitations such as delayed response, maintenance requirements, and high false alarm rates. The study emphasized the need for intelligent systems capable of analysing visual data to achieve faster and more reliable fire detection [5].

Celik proposed an image-processing-based fire detection technique that utilizes colour and motion characteristics of flames to detect fire in video sequences. In this approach, RGB images were converted into the CIE Lab* colour space to better distinguish fire pixels from background objects. Additionally, motion analysis was used to track flame movement across consecutive video frames. Although the method demonstrated promising results, its computational complexity and limited capability in detecting smoke reduced its effectiveness for real-time applications [6].
Çetin et al. conducted an extensive review of video-based fire detection systems and highlighted the advantages of combining surveillance cameras with advanced video processing techniques. Their research showed that video-based systems can detect fire earlier than traditional sensor-based approaches by analysing visual patterns such as flame flickering, smoke movement, and colour variations. However, many early video-based methods relied heavily on manually engineered features, which limited their robustness when applied to complex or dynamic environments [7].

With the advancement of artificial intelligence, machine learning techniques have increasingly been applied to fire detection problems. Dampage et al. proposed a forest fire detection system that integrates wireless sensor networks with machine learning algorithms to identify fire incidents and send alerts to nearby communities and emergency services. Their approach demonstrated improved detection performance compared to conventional sensor-based systems; however, it required extensive hardware deployment and infrastructure for sensor networks [8].

Saeed et al. introduced a multimedia surveillance system for fire detection using a hybrid machine learning approach that combines AdaBoost and Multi-Layer Perceptron (MLP) algorithms. The system analyses data collected from multiple sensors such as smoke, heat, and gas detectors to improve prediction accuracy. Although the hybrid model demonstrated improved performance, it primarily relied on sensor data rather than visual analysis from surveillance cameras [9].

Recent developments in deep learning have significantly improved the capabilities of image classification and object detection systems. Convolutional Neural Networks (CNNs) have emerged as one of the most effective deep learning models for analysing visual data. CNNs automatically learn hierarchical feature representations from images, enabling them to detect complex visual patterns such as flames and smoke without requiring manual feature extraction [10], [11], [12].

Several studies have demonstrated that deep learning models outperform traditional machine learning algorithms in fire detection tasks. CNN-based approaches have achieved higher detection accuracy, improved recall rates, and better generalization across diverse environmental conditions. Furthermore, publicly available datasets containing fire and non-fire images have supported the development and evaluation of deep learning-based fire detection systems [13]–[16].
Despite these advancements, several challenges remain in developing reliable fire detection systems.

Many existing models rely on limited datasets and may struggle to detect early-stage fires under challenging conditions such as low lighting, visual noise, or occlusions. Additionally, computational complexity and real-time processing requirements remain important considerations when deploying fire detection systems in practical environments.

To address these limitations, the present study proposes a deep learning-based fire detection system using Convolutional Neural Networks to accurately classify fire and non-fire images obtained from surveillance cameras. The proposed approach focuses on improving detection reliability through data augmentation, optimized training strategies, and robust model evaluation techniques, enabling more accurate and efficient fire detection in real-world environments.

III. SYSTEM ANALYSIS

A. Existing System

Traditional fire detection systems primarily rely on physical sensing devices such as smoke detectors, heat sensors, and gas detectors to identify the presence of fire. These systems operate by continuously monitoring environmental parameters including temperature variations, smoke concentration, and combustible gas levels. When the detected value exceeds a predefined threshold, the system triggers an alarm to alert users about a potential fire incident. Sensor-based fire detection technologies have been widely implemented in residential buildings, industrial facilities, and commercial infrastructures due to their relatively simple deployment and low initial cost [5].

Despite their widespread use, conventional sensor-based fire detection systems exhibit several limitations. Environmental disturbances such as dust, humidity, steam, fog, and cooking smoke can frequently cause false alarms. In addition, these systems typically detect fire only after significant changes in environmental conditions occur, such as a substantial increase in temperature or smoke density. As a result, the response time may be delayed, which can lead to increased damage before emergency measures are initiated [5].

With the advancement of computer vision and image processing techniques, several research studies have attempted to detect fire by analysing visual information captured from surveillance cameras. These approaches typically analyse visual characteristics such as flame colour distribution, motion patterns, and brightness variations within image sequences to identify fire regions. For example, image-processing-based fire detection techniques have utilized colour space transformations and motion analysis to identify potential fire pixels in video frames [6]. Similarly, video-based fire detection systems analyse flame flickering behaviour, smoke propagation patterns, and colour changes to detect fire incidents at an earlier stage compared to traditional sensor-based approaches [7]

However, many early computer vision-based fire detection methods relied heavily on manually engineered features, which limited their robustness in complex or dynamic environments. These handcrafted feature-based models often struggle when dealing with variations in lighting conditions, background clutter, and diverse fire characteristics across different environments.

To improve detection performance, several studies have applied traditional machine learning algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), AdaBoost, and other classification techniques to fire detection tasks. Although these models provide better performance than purely rule-based systems, they still face challenges in accurately capturing the complex visual patterns associated with fire and smoke. In many cases, these models fail to generalize effectively across different datasets and environmental conditions, leading to reduced prediction accuracy [9].

Furthermore, earlier machine learning approaches are often limited in their ability to process high-dimensional image data efficiently. Visual fire detection requires analysing complex spatial patterns within images, which traditional algorithms may not handle effectively without extensive feature engineering. Consequently, these systems may produce inaccurate predictions when confronted with diverse fire scenarios, occlusions, or visually noisy backgrounds.

These limitations highlight the need for more advanced approaches capable of automatically learning meaningful visual representations from image data. Recent advancements in deep learning and convolutional neural networks have provided promising solutions for overcoming the shortcomings of traditional fire detection systems by enabling more accurate and robust analysis of visual information [10]–[12]..

Disadvantages Of The Existing System

High False Alarm Rate:
Traditional fire detection systems may generate false alarms due to environmental disturbances such as dust, fog, steam, or lighting variations [5].
Delayed Fire Detection:
Sensor-based systems typically detect fire only after significant smoke or temperature changes occur, which may delay emergency response.
Limited Feature Extraction:
Conventional image-processing approaches depend on manually engineered features, which may not effectively represent complex fire patterns [6].
Poor Adaptability:
Traditional machine learning models often struggle to adapt to varying environmental conditions such as low lighting, reflections, or cluttered backgrounds.

Hardware Dependency:
Many fire detection systems require specialized sensors or dedicated hardware infrastructure, which increases installation and maintenance costs [8].
Inability to Handle Complex Visual Data:
Standard machine learning algorithms are not well suited for processing high-dimensional image data, limiting their performance in visual fire detection tasks.

B. Proposed System
To overcome the limitations of traditional fire detection methods, this research proposes a deep learning-based intelligent fire detection system using Convolutional Neural Networks (CNNs). The proposed system utilizes computer vision techniques to analyse images captured from surveillance cameras and automatically identify the presence of fire. Deep learning models, particularly CNN architectures, have demonstrated strong performance in image recognition and classification tasks due to their ability to automatically learn hierarchical visual features from raw image data [10]–[12].

The system begins by collecting a dataset consisting of fire and non-fire images obtained from publicly available fire detection datasets and other image sources. These datasets provide diverse visual samples of flames, smoke patterns, and normal environmental scenes, which are essential for training robust deep learning models [13]–[16]. After dataset collection, image preprocessing techniques are applied to improve data quality and ensure consistency. This preprocessing stage includes noise removal, normalization, and resizing of images to standardized dimensions suitable for deep learning model input.

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

The processed images are then fed into a CNN-based deep learning architecture. The convolutional layers extract important visual features such as flame boundaries, colour distributions, and texture characteristics associated with fire. These layers enable the model to automatically learn complex spatial patterns that distinguish fire from non-fire images. Pooling layers are used to reduce the dimensionality of feature maps while retaining essential information, thereby improving computational efficiency. Finally, fully connected layers perform the classification process by categorizing the input images into fire and non-fire classes.

To improve training performance and minimize the risk of overfitting, optimization techniques such as Early Stopping and ReduceLROnPlateau are implemented during the training process. These optimization mechanisms help stabilize the learning process and ensure that the model converges to an optimal solution with improved prediction accuracy. Once the model has been successfully trained, it can analyse real-time images or video frames captured from surveillance cameras. When the system detects the presence of fire, it activates an automatic alarm mechanism that sends notifications to users or emergency response teams. This real-time detection capability enables faster intervention and helps reduce the potential damage caused by fire incidents. Video-based fire monitoring systems have demonstrated significant advantages in early fire detection compared to conventional sensor-based approaches [7].

The proposed system offers several advantages over traditional fire detection systems. By leveraging deep learning and computer vision techniques, the system can detect fire at an earlier stage, reduce false alarms, and operate effectively in complex environments. Furthermore, the framework 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 environments [9].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

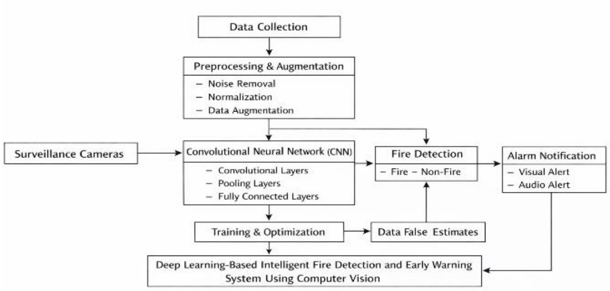

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Data Collection and Preprocessing

The first stage of implementing the proposed fire detection system involves collecting relevant image datasets containing both fire and non-fire images. These images may be obtained from publicly available fire detection datasets as well as surveillance camera footage. Several open-source datasets containing fire images and wildfire scenes are widely used for training and evaluating fire detection models [13]–[16]. The collected images are categorized into two primary classes: fire images and non-fire images, which form the basis for supervised learning.

Preprocessing techniques are applied to improve the quality and consistency of the dataset before training the deep learning model. These preprocessing steps include resizing images to a standardized resolution, removing noise, normalizing pixel values, and converting the data into formats suitable for deep learning frameworks. Proper preprocessing ensures that the dataset is clean and structured, which significantly improves the training efficiency and prediction accuracy of the model.

Feature Extraction and Data Augmentation

In this module, important visual features related to fire such as flame colour distribution, shape patterns, brightness variations, and smoke textures are extracted from the input images. Unlike traditional image-processing techniques that rely on manually designed features, deep learning models automatically learn these features during the training process. Convolutional Neural Networks (CNNs) are particularly effective in capturing spatial patterns within images and identifying complex visual characteristics associated with fire [10]–[12].

To enhance model robustness and reduce the risk of overfitting, data augmentation techniques are applied to increase the diversity of the training dataset. Augmentation methods such as image rotation, horizontal flipping, scaling, zooming, and brightness adjustment generate additional training samples from existing images. This approach allows the model to learn from multiple visual perspectives and improves its ability to generalize across different environments and lighting conditions.

Training the Deep Learning Model

The proposed fire detection system utilizes a Convolutional Neural Network (CNN) to classify images as fire or non-fire. The CNN architecture consists of multiple layers including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for final classification. Convolutional layers detect key visual patterns such as flame edges and colour gradients, while pooling layers reduce computational complexity by compressing feature maps.

During the training process, pre-processed images are fed into the CNN model and the network parameters are optimized using backpropagation and gradient-based optimization algorithms. The model learns to recognize patterns associated with fire by minimizing classification errors over several training iterations. Deep learning models have demonstrated high performance in visual recognition tasks due to their ability to learn hierarchical representations of image features [10]–[12].

Real-Time Fire Detection and Alert System

After the training phase, the trained CNN model is deployed for real-time fire detection using surveillance camera feeds. Incoming images or video frames are continuously processed by the model to determine whether they contain fire-related patterns. Video-based fire detection systems provide the advantage of monitoring large environments and detecting fire at an earlier stage compared to traditional sensor-based approaches [7].

When the system detects fire in an image frame, an automated alarm mechanism is triggered immediately. The system can generate visual alerts, audio alarms, or send notifications to responsible authorities or emergency response teams. This real-time alert capability enables rapid intervention and helps minimize potential damage caused by fire incidents.

Model Evaluation and Continuous Monitoring

To evaluate the performance of the proposed fire detection system, several machine learning evaluation metrics are used, including accuracy, precision, recall, F1-score, loss, and AUC-ROC. These metrics provide insights into the model's ability to correctly classify fire images while minimizing false detections. Evaluating multiple metrics ensures a comprehensive assessment of model reliability and robustness.

Continuous monitoring of the deployed system is also performed to maintain consistent performance under different environmental conditions. As new fire image data becomes available, the model can be retrained or fine-tuned to improve detection accuracy and adapt to emerging fire detection scenarios. Such adaptive learning capabilities enable the system to maintain reliable performance in dynamic real-world environments [9].

VI . RESULTS AND DISCUSSION

To evaluate the performance of the proposed deep learning-based fire detection system, experiments were conducted using fire and non-fire image datasets collected from publicly available sources and surveillance camera simulations. The dataset includes various visual attributes such as flame colour, smoke patterns, brightness variations, and environmental backgrounds. These visual parameters were used to train classification models capable of identifying fire incidents from image data.

The performance of the proposed system was evaluated using standard machine learning evaluation metrics including accuracy, precision, recall, and AUC-ROC. In addition, cross-validation techniques were applied during training to ensure reliable performance evaluation and reduce bias in model predictions. Cross-validation improves the model's generalization capability when applied to new images captured in real-world environments.

Experimental results indicate that the Convolutional Neural Network (CNN) model significantly outperforms traditional machine learning algorithms such as Logistic Regression, K-Nearest Neighbor (KNN), and AdaBoost. The CNN model achieved higher classification accuracy because it automatically learns complex visual features from image data such as 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 shown in Table 1, the CNN model achieved the highest performance, demonstrating superior accuracy and detection capability compared to traditional machine learning algorithms. Deep learning models are particularly effective in image-based fire detection because they can automatically learn hierarchical representations of visual features such as flame shapes, brightness patterns, and smoke textures.

The AdaBoost model also demonstrated relatively strong performance due to its ensemble learning mechanism, which combines multiple weak classifiers to improve prediction accuracy. However, traditional models such as Logistic Regression and KNN showed lower performance because they rely on manually engineered features and are less capable of capturing complex visual patterns associated with fire.

ROC Curve Analysis

To further analyse the classification performance of the models, a Receiver Operating Characteristic (ROC) curve analysis was conducted. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds.

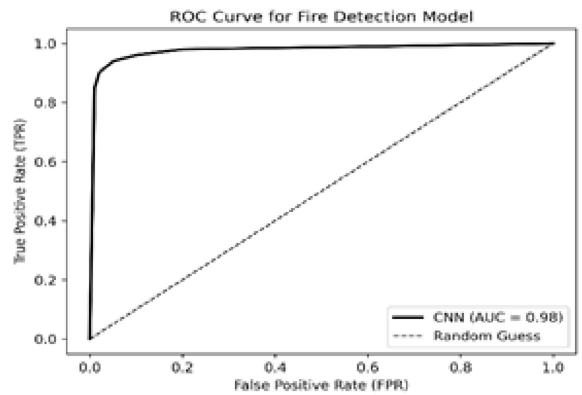

Fig. 2. ROC Curve for Fire Detection Models

The ROC analysis indicates that the CNN model achieved the highest Area Under the Curve (AUC) value of 0.97, demonstrating strong capability in distinguishing between fire and non-fire images. A higher AUC value indicates better classification performance and improved reliability in detecting fire incidents.

Overall, the experimental results demonstrate that the proposed CNN-based fire detection system provides highly accurate and reliable fire detection performance. By leveraging deep learning and computer vision techniques, the system can effectively detect fire patterns in surveillance images and significantly reduce false alarms compared to traditional detection approaches.
The results confirm that the proposed deep learning framework is suitable for real-time fire monitoring and surveillance applications, enabling faster emergency response and improved safety management in residential, industrial, and public environments.

VII. CONCLUSION

This research presented a deep learning-based intelligent fire detection system using Convolutional

Neural Networks (CNNs) for early fire identification in surveillance environments. The proposed system analyses images captured from surveillance cameras and automatically detects fire incidents by classifying images into fire and non-fire categories. Compared to traditional fire detection systems that rely on physical sensors such as smoke and heat detectors, the proposed approach offers improved detection accuracy, faster response time, and reduced false alarm rates by utilizing computer vision and deep learning techniques [5], [7].

Experimental evaluation demonstrated that the CNN-based model achieved significantly higher classification accuracy compared with conventional machine learning algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), and AdaBoost. The ability of CNN models to automatically learn hierarchical visual features such as flame shapes, brightness patterns, and smoke textures enables more reliable fire detection in complex environments [10]–[12]. In addition, the application of data augmentation techniques and training optimization strategies improved the robustness and generalization capability of the model, allowing it to perform effectively across different fire scenarios and environmental conditions.

The proposed fire detection system can be easily integrated with existing video surveillance infrastructures, providing a cost-effective and scalable solution for fire safety monitoring in residential buildings, industrial facilities, and public spaces. By enabling early fire detection and automated alert generation, the system can assist emergency responders in taking timely preventive actions and minimizing the potential damage caused by fire incidents. Intelligent surveillance-based fire detection systems have been recognized as promising alternatives to traditional sensor-based monitoring methods in modern safety management systems [9].

For future work, the proposed model can be further enhanced by training it on larger and more diverse datasets that include various fire conditions, smoke patterns, lighting variations, and environmental scenarios. This will improve the model's ability to generalize to real-world environments and reduce potential detection errors.

Additionally, advanced deep learning architectures such as ResNet, YOLO, or EfficientNet can be explored to improve both detection speed and classification accuracy. Integrating the fire detection framework with IoT-based sensor networks and cloud-based monitoring platforms could further enhance real-time fire monitoring capabilities and enable large-scale deployment in smart cities, industrial environments, and forest monitoring systems [8], [17], [18].

Overall, the integration of deep learning and computer vision techniques provides a powerful and intelligent solution for modern fire detection systems. The proposed framework demonstrates strong potential for improving fire safety monitoring and supporting rapid emergency response in real-world applications..

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