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Recent Advances in Flame Detection Using Convolutional Neural Networks: A Review

Ruibing Shi[1], Dhritiman Vaikuntan[2]

[1]University of Colorado Boulder, Boulder, USA

[2]University of Colorado Boulder, Boulder, USA

*Corresponding author: Ruibing Shi, Ruibing74@colorado.edu

Abstract: Flame detection plays a critical role in fire prevention, with early detection essential for minimizing damage and ensuring safety. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for improving flame detection accuracy, speed, and reliability. This paper reviews recent advancements in CNN-based flame detection, highlighting methods that have enhanced detection accuracy, reduced false positives, and improved dataset quality. Practical applications in areas such as forest fire monitoring, building safety, and industrial fire prevention are discussed. The review aims to encourage further research into innovative CNN-based flame detection methods to develop more efficient and effective fire detection systems.

Keywords: Flame Image Detection; Convolutional Neural Network; Recall Rate; Precision Rate; Detection Speed; Prediction Frame; Actual Object; Fire Detection.

1. Introduction

Flame detection is a critical area of research with widespread applications, particularly in fire prevention, industrial safety, and environmental monitoring. With the increasing number of fire-related incidents and their devastating consequences, early detection of flames has become an essential task to prevent the rapid spread of fire, minimize property damage, and safeguard human lives. Traditional flame detection techniques, such as optical sensors, infrared cameras, and thermal imaging systems, have proven effective in many settings. However, they often suffer from limitations, such as susceptibility to environmental interference and false alarms caused by non-fire-related heat sources.

In recent years, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have emerged as a powerful tool for image-based flame detection due to their superior ability to automatically extract and learn hierarchical features from images. CNNs have shown promising results in enhancing the accuracy, speed, and robustness of flame detection systems, making them suitable for real-time applications in complex environments. Various studies have demonstrated their effectiveness by integrating techniques such as data augmentation, multi-layer feature fusion, and transfer learning to improve the network ' s generalization ability and reduce false positive rates.

This paper aims to provide a comprehensive overview of recent advancements in flame detection using CNN-based approaches, discussing state-of-the-art techniques, their potential applications, and future research directions. Key areas of improvement include optimizing CNN architectures, leveraging attention mechanisms to focus on critical regions of images, and employing hybrid models that combine deep learning with traditional methods. Furthermore, the integration of CNNs with Internet of Things (IoT) devices and smart sensor networks has paved the way for intelligent, automated flame detection systems capable of real-time alerts and remote monitoring.

The practical applications of CNN-based flame detection are diverse, ranging from residential fire alarms and smart buildings to industrial plants, forests, and critical infrastructure. Figure 1 illustrates an example of a flame image detection scenario, highlighting the network's ability to identify flame regions accurately under varying lighting and environmental conditions.

In conclusion, with ongoing research efforts and technological advancements, CNN-based flame detection systems have the potential to significantly enhance the effectiveness of fire prevention and response strategies. This review discusses the key challenges, such as computational efficiency and robustness to environmental variations, while highlighting promising solutions for future development.

Figure 1. Example of flame image detection

2. Method

In this paper, we present a comprehensive summary of recent studies aimed at improving the performance of Convolutional Neural Networks (CNNs) in flame detection. Given the importance of reliable and efficient detection in diverse real-world scenarios, researchers have explored various innovative methods to optimize different aspects of CNN performance. These methods are categorized into four main groups: precision and recall rate improvements, detection speed optimizations, dataset quality enhancements, and practical applications in different environments. By categorizing these advancements, we aim to offer a clear and structured understanding of how each approach addresses key challenges in flame detection and contributes to overall system improvements.

The first category focuses on precision and recall rate improvements, which are critical for reducing false positives and ensuring that actual fire incidents are accurately identified. Studies in this category emphasize the development of more sophisticated network architectures, the application of attention mechanisms, and the use of multi-scale feature extraction. Techniques such as the integration of residual blocks, feature pyramid networks (FPNs), and dilated convolutions have been shown to improve the model's ability to detect small or distant flames in complex scenes. Enhanced precision and recall rates are essential for applications where false alarms can lead to costly disruptions or where missed detections could result in severe consequences.

The second category deals with detection speed optimizations, which are vital for real-time monitoring and rapid response to fire hazards. In many cases, especially in industrial and high-risk environments, detection systems must operate within milliseconds to provide timely alerts. Recent research has explored techniques such as model pruning, quantization, and the use of lightweight CNN architectures, such as MobileNet and YOLO (You Only Look Once), to achieve significant reductions in computational load without compromising detection accuracy. Studies also investigate the benefits of parallel processing and GPU acceleration to further enhance speed, making these systems practical for deployment in environments where immediate action is required.

The third category highlights dataset quality enhancements, an area often overlooked but crucial for improving model generalization and robustness. High-quality datasets containing diverse flame scenarios, lighting conditions, and environmental backgrounds are essential for training CNNs that perform reliably across a wide range of real-world conditions. Researchers have focused on collecting and curating large-scale datasets that include annotated images from different sources, such as industrial sites, forests, and residential areas. Data augmentation techniques, such as geometric transformations, synthetic data generation, and adversarial training, are also commonly used to increase dataset diversity and improve model resilience against variations in scale, angle, and occlusion.

Finally, the fourth category explores practical applications of CNN-based flame detection systems in various industries and settings. These studies assess the feasibility and effectiveness of deploying CNN models in real-world environments, such as smart buildings, factories, and outdoor fire monitoring systems. Researchers have investigated the integration of flame detection systems with Internet of Things (IoT) devices and wireless sensor networks to enable remote monitoring and automated alert mechanisms. Moreover, applications in autonomous firefighting drones and robots have demonstrated the potential for CNN-based systems to support proactive fire mitigation efforts. Field trials and case studies are also discussed, providing valuable insights into the challenges of implementation, such as power consumption, environmental noise, and maintenance requirements.

Overall, for each category, we provide a detailed summary of the key studies conducted, the methods they employed, and the resulting improvements in performance metrics, such as detection accuracy, speed, and robustness. By synthesizing these findings, this paper aims to offer a comprehensive understanding of the current state of research in CNN-based flame detection and identify promising directions for future work.

3. Results

Flame image detection using convolutional neural network is the main and most advanced means of fire detection at present. the main methods to improve the network performance are to improve the recall rate, improve the accuracy rate, improve the detection speed, and improve the coverage of the prediction frame and actual objects. The importance of these four means in the field of flame detection also decreases in turn. Accuracy rate and recall rate belong to the precision dimension, and detection speed belongs to the time dimension. Figure 2 shows the steps of flame image detection.

3.1 In Improving the Accuracy of the Algorithm

Avula et al. adopted the method of optimizing the threshold based on fuzzy entropy, and introduced the spatial transformation network (Spatial Transformer Networks) to optimize the traditional neural network, improving the accuracy and recall of the model; Dingweiqi et al. A fire video recognition method based on 3D convolutional neural network was proposed, which made full use of the timing information contained in the video for fire detection to complete the binary classification task, and finally achieved a result of 97.3%; Xu Xiaoqiang et al. The method combined with the YCbCr space model to detect the flame, and set it as a binary classification problem, achieved an accuracy rate of 94.2% in the water environment, reducing the false detection rate of areas such as flame reflections on the water surface; strict Chen et al. proposed a video flame detection method based on multi-level feature fusion, which improved the precision and recall rate of small flame detection in videos. Cao et al. proposed a video-based attention-enhanced bidirectional long-short-term memory network for smoke and flame detection in forests, making the detection accuracy of fire smoke in videos reach 97.8%; Shahid et al. Internal attention is used to optimize the convolutional neural network, and image classification is performed by aggregating features from the entire spatial background, so that the model can classify fires by detecting flames, and the accuracy rate reaches 93.70%; Xie Shuhan proposed a fire smoke detection model embedded in the channel attention mechanism based on the channel attention mechanism to realize the recognition of smoke pictures in the fire. The accuracy rate of fire smoke classification reached 92.5%, and the recall rate reached 87.7%.

3.2 In Improving the Running Speed and Reducing the Number of Parameters

Dutta et al. used the method of combining the separable volume and the digital image processing structure to optimize the parameter amount and running time of the flame image detection algorithm; Tang Danni et al. proposed A forest fire detection algorithm based on channel pruning YOLOv3 and a forest fire detection algorithm based on MobilenetV3-YOLOv4 can reduce the number of parameters to 1/6 of the original YOLOv3 algorithm while improving accuracy.

In terms of improving the quality of the data set Yang et al. proposed a flame image generation method based on a generative confrontation network, which migrated the flame image to a specific scene, thereby increasing the number of fire video samples in a restricted scene, and ensuring that the flame image in a specific scene The diversity of flames; Du Jiaxin et al. proposed a smoke generation confrontation network framework, which can effectively solve the underfitting problem caused by the lack of relevant samples in the data set in computer vision, and increase the fitting ability of the trained model.

3.3In the Application of Landing

Based on multi-sensor fusion technology, Chen Peihao et al. developed an advanced fire identification system by combining multiple cutting-edge algorithms and techniques. Their approach integrated the prospect extraction algorithm using Otsu threshold segmentation, a support vector machine (SVM) fire identification algorithm based on multi-feature fusion, and a hybrid dynamic detection algorithm. These methods were further enhanced by an improved deep learning algorithm built upon the lightweight MobileNetV3 architecture, designed to provide efficient and accurate fire detection under varying environmental conditions. By leveraging this combination of algorithms, they designed and physically implemented a fire identification system capable of high-speed processing, robust fire recognition, and real-time adaptability. The system demonstrated superior performance in detecting fires across diverse scenarios, making it suitable for applications in industrial settings, residential safety, and outdoor environments such as forests.

In another significant contribution to fire detection and prevention, Rahmatov et al. developed a state-space navigation system that integrates convolutional neural networks (CNNs) to predict the size and intensity of fires accurately. This system incorporates CNNs to analyze real-time sensory data and predict the growth trajectory of the fire with high precision. To further enhance the system's utility in fire control and rescue operations, they employed a greedy algorithm to compute the most probable routes for fire spread based on environmental parameters such as wind speed, topography, and available fuel sources. By anticipating the potential direction of fire propagation, this system provides crucial decision-making support to emergency response teams, allowing for more effective evacuation planning, fire suppression strategies, and resource allocation. As a result, it significantly alleviates the pressure on fire rescue operations and personnel evacuation efforts, improving overall safety outcomes. Together, these innovations represent significant progress in the application of multi-sensor fusion, machine learning, and real-time prediction systems for enhancing fire detection and mitigation capabilities.

4. Conclusion

This paper provides a comprehensive overview of recent advances in flame detection using Convolutional Neural Networks (CNNs), highlighting key improvements and future prospects in this field. Through an in-depth review of the latest techniques, architectures, and datasets, it is evident that the application of CNNs in flame detection has significantly enhanced various performance metrics. Specifically, CNN-based approaches have contributed to notable improvements in detection accuracy by effectively capturing intricate spatial and temporal patterns of flames. Moreover, these methods have shown substantial reductions in false positive rates, which is critical for ensuring reliable operation in real-world settings. Enhanced detection speed has further facilitated real-time monitoring and decision-making, making CNN-based systems well-suited for dynamic and high-risk environments. Additionally, advancements in dataset quality, including the integration of diverse and large-scale datasets, have bolstered model generalization and robustness across different environments and flame scenarios.

The practical applications of these improvements are extensive, spanning critical areas such as forest fire monitoring, where early detection can prevent large-scale ecological disasters, building safety systems designed to protect lives and infrastructure, and industrial safety mechanisms that mitigate risks in manufacturing and hazardous settings. This review not only highlights the current achievements in the field but also underscores existing challenges, such as handling occluded or low-visibility flames, ensuring robustness across varying environmental conditions, and optimizing computational efficiency for edge deployment. By addressing these issues, future research can focus on developing next-generation CNN-based flame detection systems that combine high accuracy with low latency.

We hope that this review will serve as a valuable resource for researchers and practitioners, inspiring further innovation and collaboration. By encouraging the exploration of hybrid models, transfer learning, and attention mechanisms, this work aims to drive the development of more effective and efficient flame detection solutions capable of meeting the demands of diverse real-world applications.

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