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Current Advances in Flame Detection using Convolutional Neural Networks

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Abstract

Flame detection using convolutional neural networks (CNNs) is currently the most advanced and widely used method for detecting fires. Improving CNN performance typically involves increasing recall and precision rates, improving detection speed, and enhancing the overlap between predicted and actual objects. In this paper, we review recent advances in flame detection using CNNs, focusing on precision and recall rate improvements, detection speed optimizations, dataset quality enhancements, and practical applications.

Keywords

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

1. Introduction

Flame detection is an important field of research that has received much attention in recent years, with the aim of detecting fires early to prevent their spread and reduce damage. The use of CNNs has proven to be highly effective for flame detection, and recent studies have sought to improve CNN performance using various methods. This paper aims to provide an overview of recent advances in flame detection using CNNs and their potential applications. Figure 1 shows an example of flame image detection.

Figure 1. Example of flame image detection

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2. Methods

In this paper, we summarize recent studies that have improved CNN performance in flame detection. These studies are categorized into four groups based on the methods used: precision and recall rate improvements, detection speed optimizations, dataset quality enhancements, and practical applications. For each group, we provide a brief summary of the studies conducted and their results.

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.

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3.3 In the Application of Landing

Based on the multi-sensor fusion technology, Chen Peihao et al. used the prospect extraction algorithm of Otsu threshold segmentation, SVM fire identification algorithm of multi-feature fusion, hybrid dynamic detection algorithm, etc., improved the deep learning algorithm based on MobileNetV3, and designed and physically implemented a set of fire identification system. Rahmatov et al. developed a state-space navigation system, which can predict the size of the fire by using convolutional neural networks and further calculate the possible spread route of the fire by using greedy algorithm, thus reducing great pressure on fire rescue and personnel evacuation.

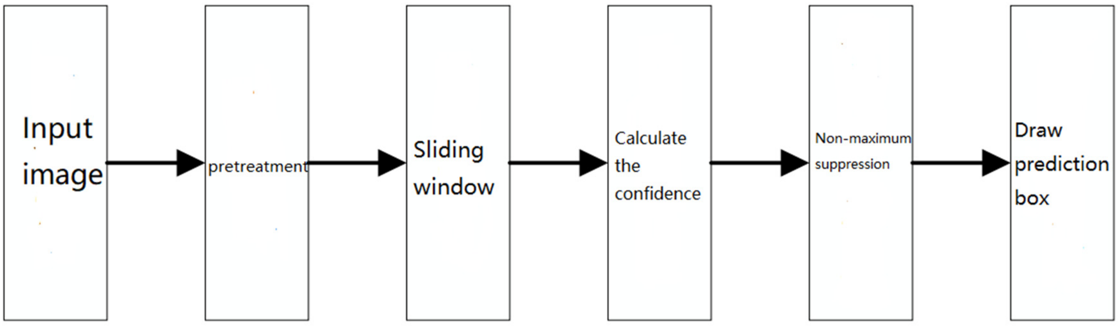

Figure 2. Step of flame image detection

4. Conclusion

This paper provides an overview of recent advances in flame detection using CNNs. Through this review, it is clear that the use of CNNs in flame detection has improved detection accuracy, reduced false positives, increased detection speed, and enhanced dataset quality. These improvements have led to practical applications in various areas, such as forest fire detection, building safety, and industrial safety. We hope that this review will inspire further research in the field of flame detection and encourage the development of more effective and efficient CNN-based flame detection methods.

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