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Article

Enhanced Fire Detection and Precise Localization in Video Surveillance Systems Using Advanced Deep Convolutional Neural Networks

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Abstract: This study focuses on enhancing fire detection and localization in video surveillance systems through advanced deep convolutional neural networks (CNNs). The primary objective is to improve the precision and efficiency of fire detection in CCTV footage while maintaining low computational overhead. By utilizing the GoogleNet architecture, the proposed model detects fire features and localizes fires more accurately, enabling faster emergency responses. The research was tested on benchmark fire datasets, with experimental results showing that the model outperforms existing fire detection methods in terms of accuracy and response time. This system offers enhanced reliability for fire detection, making it suitable for real-world applications in surveillance systems to prevent fire-related disasters.

Keywords: Video Surveillance Systems; Neural Networks; Heterogeneous Dataset; Low Computing Overhead; Surveillance Systems; Benchmark Fire Datasets;

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1. Introduction

The increased processing capabilities embedded in modern smart devices have led to smarter surveillance systems, which are now used in various domains such as e-health, autonomous driving, and event monitoring. During surveillance, various abnormal events can occur, such as fires, accidents, disasters, medical emergencies, fights, and floods. Timely detection of these events is critical to minimizing the potential for disasters and controlling them before they escalate, thereby reducing losses [1]. Among these abnormal events, fires are one of the most common occurrences. Detecting fires at an early stage during surveillance can prevent home fires and large-scale fire disasters. Along with other factors, physical disabilities are a significant concern in home fires, ranking second as a factor affecting fire victims, with 15% of home fire victims affected by disabilities. According to the 2015 NFPA report, approximately 1,345,500 fires occurred in the United States, resulting in $14.3 billion in damages, 15,700 civilian fire injuries, and 3,280 civilian fire fatalities. A civilian fire injury and death occurred every 33.5 minutes and every 160 minutes, respectively. Moreover, 78% of these fire deaths occurred due to home fires, primarily because of delayed escape for disabled individuals. Traditional fire alarm systems often rely on detecting strong flames or proximity, making them inefficient for individuals with disabilities who require timely alarms [2-6]. This highlights the need for more effective fire alarm systems in surveillance, especially to assist individuals who may struggle to escape in emergencies.

Most modern fire alarm systems are based on vision sensors, given their affordability and ease of installation. Consequently, much research has focused on fire detection using cameras. The increasing importance of early fire detection has driven advancements in surveillance technology, and with the integration of deep learning techniques, the potential for more accurate fire detection has significantly increased [7-12]. This project aims to address the limitations of traditional fire detection methods by utilizing a deep learning-based framework for flame detection in CCTV surveillance videos. We propose a cost-effective CNN framework that eliminates the need for tedious and time-consuming manual feature engineering, allowing the model to automatically learn rich features from raw fire data [13-19]. This approach is particularly beneficial as it simplifies the process of fire detection and makes the system more efficient. Inspired by transfer learning strategies, we fine-tuned a model with an architecture similar to GoogleNet for fire detection, outperforming traditional fire detection schemes. The proposed framework strikes a balance between detection accuracy and computational complexity while also reducing the number of false alarms compared to state-of-the-art fire detection methods. As a result, our framework is well-suited for early flame detection in surveillance scenarios, helping to prevent fires before they escalate. The rest of this project explores our proposed architecture, presents experimental results, and discusses the future directions for improving fire detection systems [20-25].

In the context of rapid economic development, the increasing scale and complexity of modern constructions have introduced significant challenges in fire control. Early fire detection, combined with high sensitivity and accuracy alarms, is essential to reduce fire-related losses. Recently, image-based fire detection has gained popularity due to its advantages, including early fire detection, high accuracy, flexible system installation, and the ability to effectively detect fires in large spaces and complex building structures. Developing an algorithm based on CNN is essential to meet these growing needs. In this project, we develop an algorithm where surveillance cameras detect fires and immediately send alerts to people, enabling rapid responses to prevent further damage [26-31].

Our approach evaluates the performance of fire localization and scene understanding under surveillance. By computing the true positive and false positive rates, we assess the accuracy of fire localization. The feature maps used to localize fires are smaller than the ground truth images, so they are resized to match the size of the ground truth images [32-39]. We then compute the number of overlapping fire pixels in the detection maps and ground truth images, which are categorized as true positives. Similarly, non-overlapping fire pixels are categorized as false positives. One of the key advantages of using SqueezeNet in this project is its ability to generate larger feature maps using smaller kernels and avoiding pooling layers. This allows for more accurate localization of fire, improving the system’s overall effectiveness in detecting and responding to fire emergencies [40].

Deep learning, a subset of machine learning, is essential to this project. It involves neural networks with multiple layers that attempt to simulate the behavior of the human brain to some degree, allowing machines to "learn" from large datasets. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help optimize the network's accuracy. Deep learning is the driving force behind many artificial intelligence (AI) applications and services, enabling automation in various domains. These applications perform both analytical and physical tasks without human intervention. Deep learning technology powers everyday products and services, such as digital assistants, voice-enabled remotes, and credit card fraud detection systems [41-44]. It also supports emerging technologies, including self-driving cars and automatic CCTV camera-based fire detection systems.

The aim of this project is to develop an algorithm that can detect fires quickly using surveillance cameras. We explore image-based fire detection algorithms built on advanced object detection CNN models such as Faster-RCNN, R-FCN, SSD, and YOLO V3. A comparison between the proposed algorithm and current algorithms reveals that the accuracy of fire detection based on object detection CNNs is significantly higher than other methods. In particular, the average precision of the algorithm based on YOLO V3 reaches 83.7%, which is superior to the other proposed algorithms. This increased accuracy makes our approach more reliable for detecting fires in real-time surveillance footage [45-51].

The proposed methodology for this project consists of several key phases, including image and source acquisition, pre-processing, fire detection, and searching databases for alerting individuals. The system first captures video footage from surveillance cameras and pre-processes the data to enhance the quality of the images. This is followed by the fire detection phase, where the deep learning model identifies potential fire instances in the footage. Once a fire is detected, the system cross-references the detection data with existing databases and generates alerts to notify individuals of the potential danger [52-61]. This process allows for a comprehensive and efficient detection and response system that minimizes the risk of false positives while maximizing the speed and accuracy of fire detection.

By implementing the CNN-based fire detection framework, we aim to address the key challenges associated with fire detection in complex environments. The use of advanced deep learning techniques ensures that the system is capable of accurately detecting fires in large and complex spaces, making it ideal for use in modern building structures. Furthermore, the system's ability to reduce the number of false alarms makes it a more practical solution for real-world applications, where false alarms can cause unnecessary panic and disruptions [62-67].

Overall, this project presents a significant advancement in fire detection technology, utilizing state-of-the-art deep learning techniques to improve the speed and accuracy of fire detection in surveillance systems. The integration of advanced CNN models, such as YOLO V3, ensures that the system is capable of providing real-time alerts with high precision, making it an effective tool for preventing fires and mitigating fire-related damage [69-74]. The use of image-based detection algorithms further enhances the flexibility and scalability of the system, allowing it to be easily integrated into existing surveillance infrastructure. Through this project, we hope to contribute to the development of more reliable and efficient fire detection systems that can help save lives and protect property in the event of a fire emergency.

Literature Review

A unique framework has been developed for utilizing Convolutional Neural Networks (CNNs) in fire detection within video surveillance systems. CNNs have proven highly effective in image classification and other computer vision tasks, and their application in fire detection systems can significantly enhance detection accuracy. This improvement in accuracy can help prevent severe fire disasters and mitigate ecological and social consequences. Despite these benefits, deploying CNN-based fire detection systems in real-time surveillance networks poses challenges due to the substantial memory and processing power required for inference. This research highlights both the potential advantages and the limitations that need to be addressed for implementing CNNs in fire detection within everyday surveillance systems, particularly in scenarios requiring immediate response [68].

Another approach to fire detection involves a time-efficient CNN model that is enhanced by transfer learning strategies. This method focuses on improving fire detection performance in surveillance applications by reducing computational overhead while maintaining high accuracy. The CNN architecture used is optimized to minimize the time needed for fire detection, making it suitable for real-time surveillance systems. Transfer learning enables the model to leverage pre-trained networks and quickly adapt to new tasks without the need for extensive retraining. This approach is particularly useful in time-sensitive applications where speed and efficiency are critical. The proposed model strikes a balance between computational demands and detection accuracy, making it applicable in real-world environments where rapid fire detection is essential [75].

An efficient deep learning framework has been designed to improve fire detection in complex surveillance environments. This system, called E-firenet, offers a robust solution to the challenges posed by large-scale surveillance networks where detecting fire incidents in real-time is crucial. The framework is designed to handle diverse environmental conditions, where traditional fire detection systems may struggle due to noise or occlusions. The system's deep learning capabilities allow it to learn from various fire incidents and accurately detect fires, even in challenging circumstances. This study emphasizes the value of integrating advanced CNN models into fire detection systems to enhance both efficiency and effectiveness in complex surveillance environments that require continuous monitoring [76].

Recent advancements in sensor technology have been utilized to enhance fire detection in video surveillance systems. Modern sensors can significantly improve the accuracy and reliability of fire detection by complementing visual data captured by surveillance cameras with additional layers of information, such as temperature or smoke levels. This combination of sensors and CNN models enhances the system’s ability to detect fires more precisely, reducing the occurrence of false positives and improving response times. This approach is particularly useful in environments where traditional visual detection methods may not be sufficient, offering a more comprehensive solution to fire detection [77].

A robust fire detection model has been developed using CNNs integrated into an intelligent robot vision system. This approach allows for accurate and autonomous fire detection through the robot's camera, offering significant potential for industries that rely on robotics for monitoring and surveillance. The model processes visual data in real-time, enabling robots to detect fire incidents without human intervention. This technology can enhance safety across various sectors, from industrial settings to public spaces, by providing real-time fire detection capabilities. The integration of CNN-based fire detection with intelligent robotic systems offers an innovative solution to improving fire safety and response times in critical environments [78].

Project Description

Traditional fire detection systems rely on electronic sensors that detect fire or smoke by measuring changes in temperature. The sensors identify the presence of fire or smoke through radiation heat, which is typically effective in small to moderate spaces. However, for large areas like petrochemical plants, sawmills, or remote factory industries, the installation and maintenance of sensors pose significant challenges. These sensors are often difficult to deploy over vast areas, making them less suitable for large-scale surveillance. Additionally, the harsh environmental conditions in remote industrial locations can further complicate the installation, functionality, and maintenance of these sensors. As a result, traditional sensor-based fire detection systems are not always the best solution for large, expansive facilities, and alternative approaches are required.

In recent years, the majority of fire detection research has focused on traditional feature extraction methods for flame detection. These methods attempt to analyze specific features of fire or smoke to determine their presence. While these methods can be effective in certain environments, they come with several drawbacks. The most significant issue is that traditional feature extraction is a time-consuming process, involving extensive manual efforts to design and extract relevant features. Additionally, their performance in detecting flames is often suboptimal, especially in complex environments with varied lighting, shadows, or fire-colored objects. In surveillance systems, such conditions can easily confuse the detection algorithms, resulting in a high number of false alarms. This is particularly problematic in areas with dynamic environments, where fluctuating lighting conditions or objects resembling flames may frequently trigger false alerts. These false alarms not only disrupt the operation of fire detection systems but also reduce trust in their reliability and accuracy [79-82].

To address these limitations, deep learning architectures have been extensively studied and explored for early flame detection. Deep learning offers a more robust and flexible approach by automatically learning relevant features from raw data. Unlike traditional methods that require manual feature engineering, deep learning models, particularly Convolutional Neural Networks (CNNs), can automatically identify patterns in fire imagery, making them more adaptable to various environmental conditions. These models are capable of detecting subtle changes in surveillance footage, even in challenging conditions with shadows, varying light intensities, or the presence of fire-colored objects. By learning from vast datasets, deep learning models can significantly reduce the occurrence of false alarms, providing a more accurate and reliable solution for flame detection. Incorporating deep learning into fire detection systems has the potential to revolutionize the industry, particularly for large-scale surveillance operations in industrial settings. These models can process large amounts of visual data in real time, allowing for faster and more accurate detection of fire incidents [83-87]. Additionally, deep learning systems can continue to improve their accuracy as they are exposed to more diverse datasets, ensuring that they remain effective even in complex or evolving environments. As industries increasingly adopt smart surveillance technologies, deep learning-based fire detection systems offer a promising solution to the limitations of traditional sensor-based methods, enhancing safety and reducing the risk of large-scale fire disasters (Figure 1).

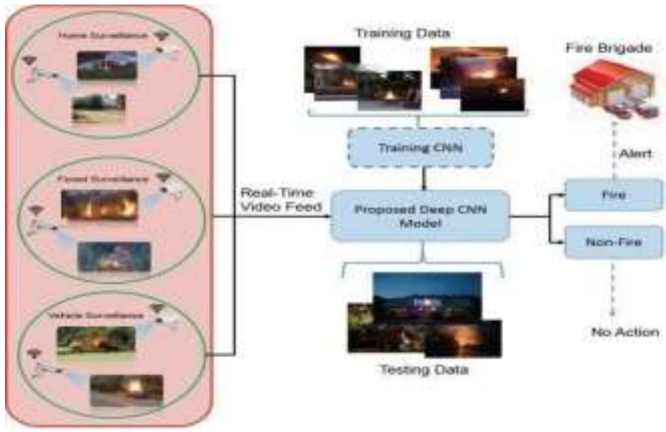

Figure 1. Module Diagram

2. Materials and Methods

Dataset Collection

The dataset used in this study was sourced from publicly available benchmark fire detection datasets, which consist of various fire and non-fire images and videos from real-world surveillance footage. The dataset was compiled to include a diverse range of environments, lighting conditions, and fire intensities to ensure the robustness of the fire detection model. The dataset was split into training, validation, and testing sets to evaluate the model’s performance comprehensively.

Preprocessing

The raw video data underwent preprocessing steps to enhance the quality of the input images and reduce noise. These steps included resizing images to a standard input size compatible with the deep learning model, normalizing pixel values, and augmenting the dataset with transformations such as rotations, flips, and brightness adjustments. These techniques were employed to ensure the model's robustness against variations in input data, which is crucial for real-world fire detection.

Deep Learning Model Architecture

The study utilized a deep convolutional neural network (CNN) based on the GoogleNet architecture, which is known for its efficient performance in computer vision tasks. This model was chosen for its balance between computational efficiency and accuracy in detecting complex features. The architecture includes multiple convolutional layers, pooling layers, and fully connected layers. Transfer learning was employed by initializing the model with pre-trained weights on a large dataset and then fine-tuning the model on the fire detection dataset to improve its fire detection capabilities.

Training the Model

The CNN model was trained using the training dataset with labeled fire and non-fire instances. The training process was carried out using cross-entropy loss as the loss function and the Adam optimizer for faster convergence. A batch size of 32 and an initial learning rate of 0.001 were selected. The learning rate was adjusted dynamically based on the validation loss to improve training stability. The model was trained for 50 epochs, with early stopping implemented to prevent overfitting.

Fire Detection and Localization

To enhance fire detection, the model integrated fire localization techniques using feature maps from intermediate CNN layers. These maps were resized to match the input image dimensions, and fire regions were identified by detecting overlapping fire pixels between the feature maps and ground truth. A bounding box was drawn around the detected fire regions, allowing for accurate localization within the video footage.

Evaluation Metrics

The model's performance was evaluated using metrics such as precision, recall, F1-score, and accuracy. The precision metric measured the model’s ability to correctly identify fires, while recall assessed how well the model detected all actual fire instances. The Intersection over Union (IoU) was used to evaluate the accuracy of fire localization by comparing the predicted bounding boxes with ground truth annotations. A high IoU score indicates precise localization of fire regions.

Implementation and Tools

The implementation of the model was carried out using the TensorFlow and Keras deep learning frameworks. The experiments were conducted on a machine equipped with an NVIDIA GPU to accelerate the training and inference processes. OpenCV was used for handling video streams and visualizing fire detection and localization results.

3. Results and Discussion

Fire detection systems have become essential in high-traffic areas and places with large crowds, as they help prevent accidents before they happen by continuously monitoring the environment. The simple act of recording and analyzing fire-related incidents can be enough to stop potential disasters from escalating. These systems are also incredibly beneficial for law enforcement agencies, such as the police, who can review the stored data for any suspicious fire-related activities. By temporarily storing data, the system provides a comprehensive input of all types of fires, allowing for a more thorough analysis and response. Fire detection systems also contribute to public safety on a smaller scale, offering protection in open workplaces and public areas with heavy traffic. In these environments, the system can detect and manage fire hazards, ensuring public safety and minimizing risks [88-92].

One innovative approach in this field is the development of an automatic fire detection system based on Convolutional Neural Networks (CNNs). In this system, CNN layers are used to segment video footage, with the objective of detecting fires and sending alert messages to users at an early stage. The architecture includes fully connected layers with seven branches, each acting as a specialized classifier that identifies specific characteristics of the input fire image captured by a camera. This method has proven effective because it minimizes errors generated during the segmentation step, providing a more reliable end-to-end solution for fire detection. The ability to extract detailed information from video footage enhances the system's performance and increases the chances of timely fire detection.

Another study introduced an automatic fire detection system for intelligent surveillance using video cameras. This system employs advanced video processing techniques such as counter matching and edge detection to accurately identify fires. The proposed method has achieved an impressive average accuracy of 94.67%, showcasing its effectiveness in real-world applications. This high level of accuracy is particularly important in environments where early fire detection is critical for safety. Additionally, the use of color edge detection, specifically the RGB method combined with channel scale-space techniques, has been proposed as an effective means of fire detection. These techniques help to distinguish fire-specific characteristics in various lighting conditions, further improving the system's ability to detect and respond to fire incidents in a timely manner.

Overall, the integration of advanced techniques like CNNs and video processing in fire detection systems represents a significant improvement over traditional method. These systems not only enhance the accuracy of fire detection but also offer valuable support for public safety initiatives in busy areas and workplaces. With continued development and optimization, such systems will likely play an increasingly important role in preventing fire-related accidents and ensuring public safety in both urban and industrial settings.

4. Conclusion

Looking to the future, video image detection (VID) is expected to become a mainstream technology in fire detection systems. By using advanced analytics, the system will be able to isolate and detect images of smoke or flames within a specific room or area. Furthermore, the VID system will have the capability to determine if individuals are present within the space, and by integrating with notification appliances, it can provide them with an optimal path for evacuation. This evolution of fire detection represents a significant advancement over earlier systems, which relied solely on sensors and lacked the ability to visually detect fires. The integration of video technology enhances the ability to identify fires at an earlier stage, offering a more proactive approach to fire safety. This not only increases the effectiveness of surveillance systems but also ensures that potential fire disasters can be mitigated in a timely manner, protecting both lives and property.

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