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INDOOR FIRE LOAD RECOGNITION USING IMAGE DATASET

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Abstract- For building safety design and resilience assessments, accurate fire load data is essential. Traditional fire load estimating techniques, including fire load surveys, take a lot of time, are laborious, and are prone to mistakes. This research suggests a vision-based way to automatically detect indoor fire load using deep learning-based instance segmentation as a first step in solving this issue. First, several categories of indoor components are determined by the materials they are made of. The development of an interior scene image collection with instance annotations follows. Finally, a model for pixel-level fire load detection is created using CNN). Results demonstrate that our model is capable of segmenting the dataset with a promising accuracy of training model.

Keywords- fire safety; fire load detection; performance-based design; deep learning; instance segmentation; pixel-level detection; indoor scene; building resilience.

1 INTRODUCTION

Building fires are one of the most common natural catastrophes in cities, causing fatalities and significant property damage. The CTIF World Fire Statistics Center estimates that there are 7 to 8 million uncontrolled fires worldwide every year. According to the Chinese Fire Statistical Yearbook there were 395052 fires in China in 2014, which resulted in 1815 fatalities, 1513 injuries, and a cost of 4.7 billion Chinese Yuan[1]. This represents an increase in economic damage of about 2.4 times since 2010. Modern commercial structures are typically huge in scale, composed of synthetic materials, crowded, have a lot of electrical equipment, and have complicated functional zones. Consequently, preventing and putting out indoor fires[2].

A Range of Sensors has recently been introduced for a number of applications, including sending off a fire alarm, detecting vehicle obstacles, viewing the interior of the human body for diagnosis, animal and ship monitoring, and surveillance[3]. Surveillance is the application that has drawn the most attention from researchers due to the greater embedded processing capabilities of cameras. Various abnormal events, such as traffic accidents, fires, medical emergencies, and so on, can be identified early using smart surveillance systems, and the proper authorities can be notified autonomously[4]. A fire is an unusual occurrence that can do major harm to people and property in a short period of time. Human error or a system breakdown are the most common causes of such disasters, which result in significant loss of human life and other harm[5]. Each year, fire disasters harm 10,000 km2 of vegetation zones in Europe; in the United States, fire disasters affect 100,000 km2 of vegetation zones each year[6].

2 MOTIVATION

Visual-based approach of image or video processing was shown to be more reliable method to detect the fire since the closed-circuit television (CCTV) surveillance systems are now available at many public places, can help capture the fire scenes. In order to detect fire from scenes of color-videos, various schemes have been studied, mainly focus on the combination of static and dynamic characteristics of fire such as color information, texture and motion orientation, etc.

3 PROBLEM STATEMENT

For building safety design and resilience assessments, accurate fire load data is essential. Traditional fire load estimating techniques, including fire load surveys, take a lot of time, are laborious, and are prone to mistakes. That security purpose We can generate the alert for the fire indoor environment.

For safety design and resilience evaluation of buildings, accurate fire load (combustible object) information is essential. Traditional fire load acquisition techniques, including fire load surveys, which take a long time and are prone to mistakes, were unable to adapt to dynamically altered indoor scenes. Fast recognition and detection of interior fire load are crucial as a starting point for computerized fire load estimate. As an outcome, this project proposal a dataset including photos of indoor scenes and descriptions on detection and segmentation.
Deep learning applied to computer vision and convolutional neural networks (CNN) development enabled quicker and usually more accurate identification. This is because a CNN can extract features and classify them all at once. By eliminating the need to manually construct feature extraction methods, this frees up time and reduces training time. Numerous studies have examined the use of this capability for fire detection, demonstrating that CNN can outperform some applicable traditional video fire detection techniques. Such research, however, focus on the outdoors, mainly forest fires. Indoor fire detection has received very little research attention, particularly in office environments.

When implementing vision-based systems, indoor environments like workspaces provide a variety of difficulties, such as obstructions obstructing the view to the intended detection region and reflections that could obstruct vision-based fire detection.

4 RELATED WORK

In order to detect and alarm early fire timely and effectively, traditional temperature and smoke fire detectors are vulnerable to environmental factors such as the height of monitoring space, air velocity, dust. An image fire detection algorithm based on support vector machine is proposed by studying the features of fire in digital image. Firstly, the motion region is extracted by the inter-frame difference method and regarded as the Suspected fire area. Then, the uniform size is sampled again[7]. Finally, the flame color moment feature and texture feature are extracted and input into the support vector machine for classification and recognition. Data sets were formed by collecting Internet resources and fire videos taken by oneself and the trained support vector machine was tested. The test results showed that the algorithm can detect early fire more accurately.

Convolutional neural networks (CNNs) have yielded state-of-the-art performance in image classification and other computer vision tasks. Their application in fire detection systems will substantially improve detection accuracy, which will eventually minimize fire disasters and reduce the ecological and social ramifications. However, the major concern with CNN-based fire detection systems is their implementation in real-world surveillance networks, due to their high memory and computational requirements for inference[8]. In this paper, we propose an original, energy-friendly, and computationally efficient CNN architecture, inspired by the SqueezeNet architecture for fire detection, localization, and semantic understanding of the scene of the fire. It uses smaller convolutional kernels and contains no dense, fully connected layers, which helps keep the computational requirements to a minimum. Despite its low computational needs, the experimental results demonstrate that our proposed solution achieves accuracies that are comparable to other, more complex models, mainly due to its increased depth. Moreover, this paper shows how a tradeoff can be reached between fire detection accuracy and efficiency, by considering the specific characteristics of the problem of interest and the variety of fire data.

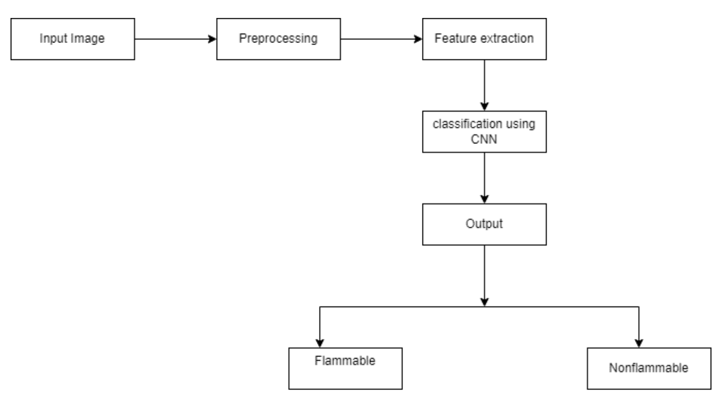
Fire is a major disaster in the world, and the fire detection system should accurately detect the fire in the shortest time to reduce economic loss and ecological damage. Traditional sensors are still widely used in a large number of applications, but they do not perform well in remote high-dome environments or the early stages of low-flame fires, and now the method of using image and video to predict fire is becoming more and more popular. This paper proposed an improved YOLOv4 fire detection method based on Convolutional Neural Networks (CNN). We improve the accuracy of the model through the self-built high-quality fire dataset, use the changed loss function to improve the detection ability of small-scale flames, and combine the Soft-NMS post-processing and DIoUNMS post-processing to improve the suppression effect of the redundant Bounding box and reduce low recall rate[9]. The experimental results of the model on our dataset show that the model has an excellent performance in fire detection and can detect multi-scale fire in real-time.

One of smart home function is fire alert detection[10]. The symptom detection of fire in the house is important action to prevent the mass fire and save many things. This research applies the new system of fire detection using gas leak concentration to predict the explosion and fire earlier called fire predictor and the fire appearance detector. The fire predictor just shows the gas leak concentration and make an alarm rang. The fire detector uses fuzzy system to make the fire detector classification. The output simulation system can send the data to MFC, but the MFC reader cannot parse it in real time.

In order to make up for the shortcomings of traditional fire detectors and improve the reliability of fire alarm, based on the Raspberry Pi hardware conditions and the Kera's deep learning framework, this paper uses the lightweight direct regression detection algorithm YOLO v3- tiny to implement a small local video identification system for ship fire[11]. Based on video test and fire simulation, the RpiFire system has achieved high accuracy in high recall rate and can meet the needs of ship fire detection.

5 SYSTEM DESIGN

System Architecture:



Recent advancements in image processing have allowed vision-based systems to detect fire using Convolutional Neural Networks during surveillance. Two custom CNN models have been implemented for a cost-effective fire detection CNN architecture for surveillance videos. To balance the efficiency and accuracy, the model is fine-tuned considering the nature of the target problem and fire data. We are going to use three different datasets for training our models.

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Our project input as video then Preprocessing refers to all the transformations on the raw data before it is fed to the machine learning or deep learning algorithm. For instance, training a convolutional neural network on raw images will probably lead to bad classification performance CNN is a neural network that extracts input image features and another neural network classifies the image features. The input image is used by the feature extraction network. The extracted feature signals are utilized by the neural network for classification.

CNN (Regions with CNN feature) is one representative work for the region-based methods. It performs the semantic segmentation based on the object detection results. To be specific, CNN first utilizes selective search to extract a large quantity of object proposals and then computes CNN features for each of them. The convolutional neural network (CNN) is a class of deep learning neural networks. CNNs represent a huge breakthrough in image recognition. They're most commonly used to analyze visual imagery and are frequently working behind the scenes in video classification.

In this proposed system, we developed a system that integrates fire color features with data about the fire's edge. Then, a parameter is established to segment out the necessary data from the photos to detect and identify the fire using the combined results from both of these procedures.

6 PROPOSED WORK

Recent advancements in image processing have allowed vision-based systems to detect fire using Convolutional Neural Networks during surveillance. Two custom CNN models have been implemented for a cost-effective fire detection CNN architecture for surveillance videos. To balance the efficiency and accuracy, the model is fine-tuned considering the nature of the target problem and fire data. We are going to use three different datasets for training our models.

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7 CONCLUSION

A deep learning-based approach for detecting the fire load indoors has been proposed by research. In order to create the dataset, interior scene photographs must first be gathered. Each instance in the images is then tagged and categorised with a material type. Second, using the CNN models are created and trained on the dataset for example segmentation. To improve the performance of the , certain training methods are presented in light of the size and distribution of the dataset. These are highly encouraging findings. A new and effective approach for automatic interior fire load detection is added to the corpus of knowledge by this study.

In that we can enhanced by training the model with a larger dataset consisting of fires at various stages and dimensions. With higher GPU memory, we could use two deep learning models for feature extraction, whose output feature vectors are concatenated and classified to offer more robustness. An CNN model can be used to implement fire localization along with classification. We can also expect better deep learning architectures to emerge in the future, offering better feature extraction. The application will also offer a considerably better performance when run on machines having better processing power compared to existing one of which it has been developed.

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