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PREVENTING FIRE HAZARDS USING CONVOLUTIONAL NEURAL NETWORKS THROUGH VIDEO CAMERAS

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ABSTRACT

Fire that is one most serious accidents in industries, public places, houses, etc. may lead to considerable production losses, equipment damages and casualties .Traditional fire detection was done by operators through video cameras in certain infrastructures. However, it is a nunrealistic job for the operator in a large facility to find out the fire in time because there may be hundreds of video cameras installed and the operator may have multiple tasks during his/ her shift. With the rapid development of computer vision, intelligent fire detection has received extensive attention from academia and industry. In this project, we present a fire detection approach through video cameras for preventing fire hazards from going out of control. The approach includes three steps: motion detection, fire detection and region classification. At first, moving objects are detected through cameras by a background subtraction method. Then the frame with moving objects is determined by a fire detection model which can output fire regions and their locations. Since false fire regions (some objects similar with fire) may be generated, a region classification model is used to identify whether it is a fire region or not. Once fire appears in any camera, the approach can detect it and output the coordinates of the fire region. Simultaneously, instant messages will be immediately sent to safety supervisors asa fire alarm. The approach can meet the needs of real-time fire detection on the precision and the speed. Its deployment will help detect fire at the very early stage, facilitate the emergency management and therefore significantly contribute to loss prevention.

Keywords: *Intelligent fire detection, Back ground subtraction method, Fire region.*

I.INTRODUCTION

The name “convolutional neural network” indicates that the network employs a mathematical operation called convolution. Convolutional networks area specialized type of neural networks that use convolution in place of general

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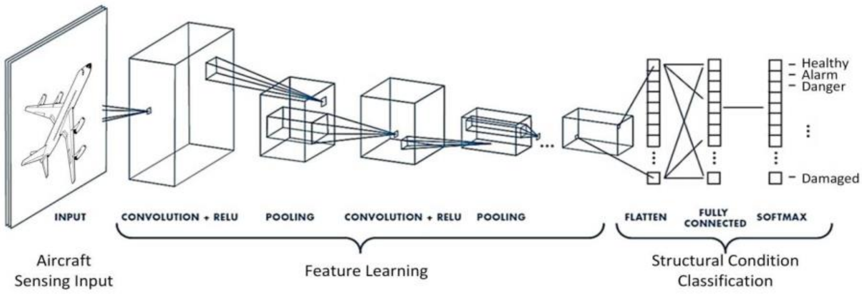
matrix multiplication in atleast one their layers.

II CONVOLUTIONAL NEURAL NETWORKS:

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of



humans and machines. Researchers and enthusiasts alike,work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision.

Fig1.1:CNN network

The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm—a Convolutional Neural Network**.**

A Convolutional Neural Network (ConvNet/CNN),represented inFigure1, is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases)to various aspects /objects in the image and be able to differentiate one from the other. The pre-processing required in a Conv Net is much lower as compared to

Other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in are stricted region of the visual field known as the Receptive Field .A collection of such fields over lap to cover the entire visual area.

Inception v3 model

The Inception network was an important mile stone in the development of CNN classifiers. Priorities inception (punintended),most popular CNNs just stacked convolution layers deeper and deeper, hoping to get better performance. Figure 1.2 represents the architecture diagram of Inception V3 model.

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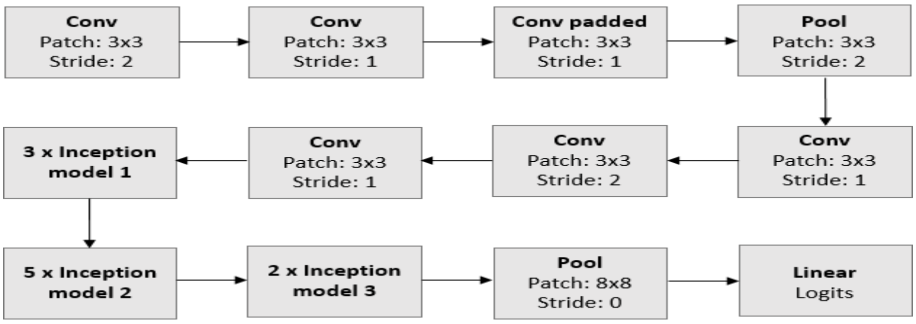

Figure1.2:InceptionV3architecturediagram

Optimizers

There is a hyper parameters that could tune to improve the performance of neural network. But, not all of them significantly affect the performance of the network. One parameter that could make the difference between algorithm converging or exploding is the optimizer choose. There are a considerable number of optimizers could choose from. Optimizers area crucial part of the neural network ,under standing how work would help to choose which one to use for the application.

III.LITERATURE SURVEY

In [1] Paulo Vinicius Koerich Borges, and Ebroul Izquierdo, proposed a new identification metric based on color for fire detection in videos. Also identified important visual features of fire, like boundary roughness and skewness of the fire pixel distribution. The skewness is a very useful descriptor as the frequent occurrence of saturation in the red channel of fire regions is identified (figure 1). For news cast videos, model the probability of occurrence of fire as a function of the back ground subtraction and coloranalysis position, yielding an efficient performance. While comparing with other methods which extract complicated features, the features discussed here allow very fast processing, making the system applicable not only for real time fire detection, but also for video retrieval in news contents, which require faster than real-time analysis.

In [2] Osman Gunay, Behçet Ugur Toreyin, proposed for image analysis. In this work assumed that several sub algorithms are combined to get the main algorithm for a specific application. Each of the sub algorithm yields its own decision to representing its confidence level. Decision values are combined with weights,updated online by using non orthogonale-projections onto convex sets describing sub algorithms. This framework is applied to a real time problem of wildfire detection. The proposed adaptive decision fusion method uses the feedback from guards of forest which is a limitation for the system.

In [3] Martin Mueller, Peter Karasev, Ivan Kolesov, and Allen Tannenbaum proposed two novel optical flow estimators, optimal mass transport (OMT) and Non-Smooth Data (NSD).The dynamics of fire have motivated the use of motion estimators to differentiate fire from other non-fire object. The obtained moving region provides useful space on which to definemotionfeatures.Thesefeaturesreliablydetectfireandrejectnon-fire motion,on a large dataset of videos. There is a chance for false detections in the presence of significant noise, partial occlusions ,and rapid angle change. the fire features are modeled by using various spatio-temporal features such as color, flickering, spatial and spatio-temporal energy. Dynamic texture analysis is use din each candidate region. The robustness of algorithm can be increased by estimation spatio-temporal consistency energy of each candidate fire region by comparing current and previous frames. The last step is to classify candidate region using SVMclassifier.

In[4]Kosmas Dimitropoulos, Panagiotis Barmpoutis and Nikos Grammalidis, proposes a fire- flame detection to be used by an early fire detection and warning system . The first step is to identify candidate fire regions using.

In [5] Pasquale Foggia, Alessia Saggese, and Mario Vento, proposes a method that is able todetectfiresbyanalysingvideos.Itintroducecomplementaryinformation,basedoncolor,shapevariation, and motion analysis, and combined using a multiexpert system known as MES. A descriptor based on a bag-of-words approach has been proposed to represent motion of objects.The method identifies moving objects based on background subtraction which is an effective method as compared to others. Then based on color, shape and movement the multi expert system works for identifying fire region.

In [6] Tian Qiu, Yong Yan and Gang Lu, a flame edge-detection method has been developed. The identification of fire edges is the process of determining a boundary between the area where there is thermo chemical reaction and those without.

First the algorithm detects the coarse and super fluous edges in a fire image and then detects the edges of the fire and removes their relevant artifacts. This flame edge-detection algorithm can contribute to the in-depth understanding and advanced monitoring of combustion flames. Also, the algorithm provides a useful addition to fire image processing and analysis in fire safety engineering. From these and a few more articles, can summarize the following as the draw backs:

- Problems arise when the objects in the camera move at more speed than the processor speed of capturing and processing the frame and hide the fire before spreading largely.
- When a bright light reflects on the camera screen, the processor wrongly recognizes it as fire and thus occurs false detection.
- Poor camera resolution, poor camera contrast ,poor signal transmission, dirty lens, vandalismetc. affects the image quality, and thus response time is delayed.
- Some systems are too complex to install, and thus the processor takes a very long time to load the image and detect. Installation cost is too high for some algorithms due to high complexity.

Thus, there is lower accuracy, delayed detection, large amount of computation, difficult installation process, weak generalization ability common in detection algorithms. Traditional algorithm depends on the manual selection of fire feature and machine learning classification. The shortcoming of algorithms is that manual feature selection should depend on professional knowledge.

IV.EXISTING METHOD

Image recognition algorithms based on convolutional neural networks(CNNs) can automatically learn and extract complex image features effectively. This kind of algorithms has attracted great concerns and achieved excellent performance on visual search, automatic driving, medical diagnosis, etc. Therefore, some scholars introduce CNNs into the field of image fire detection, thereby developing the self-learned algorithm in collection of fire image features.

Though fire detection algorithms based on CNNs have more promotion in the detection accuracy in complex scenes than traditional algorithms, some problems still exist. First,current algorithms based on machine learning mostly considered image fire detection as a classification task, and the region proposal stage was ignored. The algorithms classify the entire image toone class. However, in the early stage of fire, smoke and flame only covered a small area of the image. If the feature of smoke and flame is not obvious, use of the entire image feature without region proposals would decrease the accuracy of detection and delay fire detection and alarm activation. Therefore, proposal regions should be determined before the image classification to improve the ability of algorithm in detecting early fire. And also,some scholars designed the algorithms generating proposal regions by manually selecting features and classifying proposal regions by CNNs.This kind of algorithm, generating the proposal regions through computing individually, does not use CNNs to the global process of detection, thus leading to a large amount of computation and slow detection speed.

In this study, the image fire detection algorithm Faster-RCNN is developed and trained by the self-built fire image dataset. Finally ,optimum detection performance in the proposed algorithm Faster RCNN is determined. The results of the study can provide use full information for modification of detection algorithms for preventing fire accidents.

V. PROPOSED SYSTEM

Fire can spread easily and cause considerable losses like equipment damages & casualties. Around 9 million fire incidents and 1.2lakh deaths were recorded across the globe in2019.Of these incidents, India recorded 1.6 million fires and 27,027 deaths, according to a 195-nationanalysis by Global Diseases Burden published in The BMJ Injury Prevention journal recently. India, along with seven countries, including Pakistan, accounted for over half the deaths due to fires. The study said kids under five and adults above 60 are the biggest fire victims—a trend seen in urban India as well.35Indians died of fire accidents every day.

So, this system aims to propose a fire detection approach using convolutional neural networks through video cameras for preventing fire hazards with quick responsetime.

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VI. METHODOLOGY

Computer vision

In computer vision domain, there are three main tasks, which are image classification, object detection, instance segmentation. Among them, image classification has been studied completely with the ImageNet dataset.

Image classification aims to identify the classes of the images In this task, the performance of computers using CNN based methods has surpassed humans. Object detection aims to detect and locate objects in images. This means that the model will output the labels of objects and their coordinates. Besides, instance segmentation frames different instances from one image with object detection method, and then uses semantics different instance areas. Segmentation method to mark each pixel in different instance areas.

(a) Image classification. (b) Object detection. (c) Instance segmentation.

Figure6.1:Object detection using computer vision

Framework

This Method should train two CNN networks for the two steps. At the application stage, videos from surveillance cameras are captured and processed by the background subtraction method, which can detect moving objects from static scenes. If moving objects appear(fire is a moving object),the current frame will be processed by the trained fire detection network. The network will directly predict the probabilities and coordinates of fire regions, which are ROIs. However, in this step, the network may generate some false ROIs such as red/orange/yellow clothes,helmets, lights, etc. We continue to use the trained region classification network to identify whether each of the generated ROIs is a fire region or not.

In this way, once fire appears in the current frame, the approach can find the fire region. Simultaneously, the frame where the fire region is localized will be immediately sent to safety supervisors as a fire alarm.

Background subtraction

Video streams are captured from outdoor surveillance cameras by a computing server. Background subtraction aims to eliminate most of static image frames and retrench the resources of image computation, because the networks are computed on GPUs to accelerate the speed.

The video stream capture and the background subtraction are implemented by OpenCV, which is an open source computer vision library.

First,to eliminate the noise of images,Gaussian bluris applied on the original frames from one video stream. After that, KNN based background subtraction is implemented.

object(such as fire and humans),which is the white regions.But system can find that there are some grey regions,so webinarize this image and mark the moving object with white color.Finally, closing operatio no fmorphology is used to combine littled is crete regions into a complete region. In this way, the whole moving object is detected. In the fire detection approach, we will calculate the sizeof white regions.

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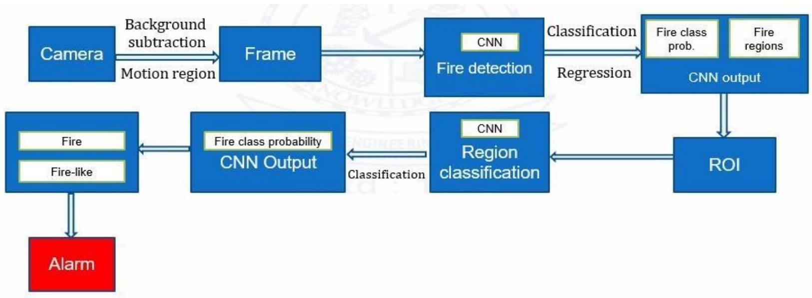
Figure6.2:Proposed System Architecture



regions into a complete region. In this way, the whole moving object is detected. In the fire detection approach, we will calculate the size of white regions in system can capture the moving The whole frame. method will set a threshold and if the size of moving objects exceeds the threshold, the next detection steps will be implemented.

Fire detection

The fire detection model is one of the key steps in our approach. This model will process the frames with moving objects from the background subtraction step and generate the ROIs where fire may exist. The fire detection model is developed by YOLO method. YOLO frames object detection as a regression problem to spatially separated bounding boxes and associated class probabilities. It trains a single neural network like CNN to predict bounding boxes and class probabilities directly from images in one evaluation. It is designed for multi-object detection, however, fire detection is a single-object(fire)detection task.

Region classification

In this step, design a CNN model to distinguish there all fire regions(positive)from the fire-like regions(negative),which is a typical classification task. Since the input size of CNN model is fixed, the generated ROIs with different width and height need to be resized to 256 × 256pixels. Then each of the resized regions will be computed through a single CNN model. Inception modules mainly increased the width of the network while keeping the computational. Budget constant. Residual module over came the training problem

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of deeper neural networks, and made it possible to train the networkwith100oreven1000layers.

VII. Output Graph Comparison

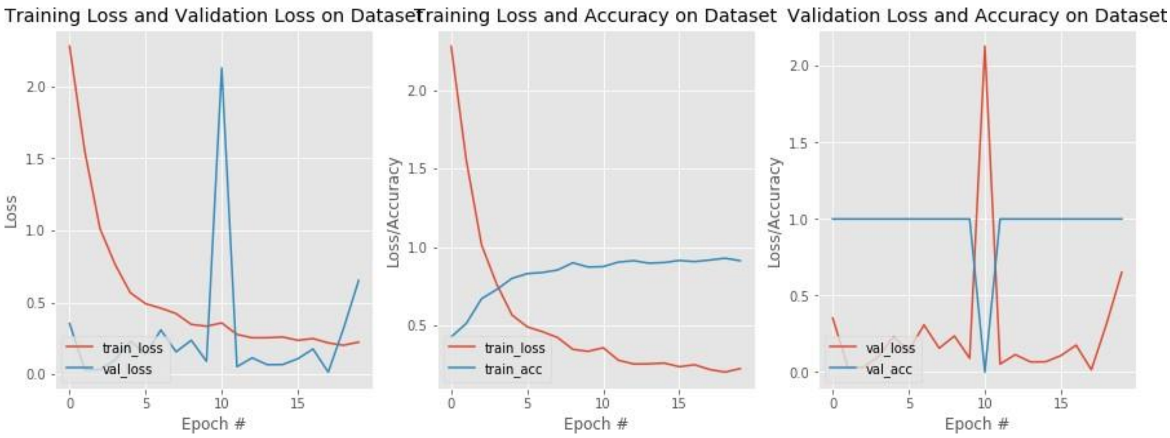

Figure7.1: InceptionV3 ModelOutput

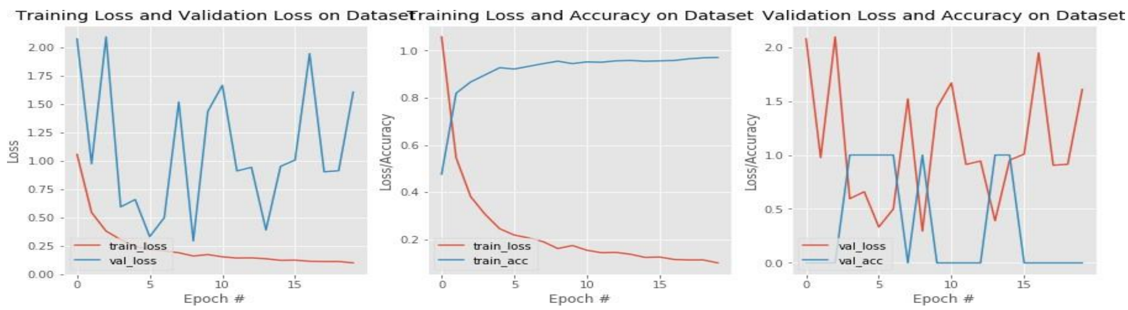

Figure7.2: Resnet 50+Vgg16 Model Output

VIII.CONCLUSION AND FUTURE SCOPE

In this work, present an intelligent fire detection approach through cameras based on computer vision methods. First, videos from surveillance cameras are processed frame by frame through a background subtraction method. If moving objects appear, the frame will be detected whether fire exists or not by the trained networks. And will be immediately sent to safety supervisors as afire alarm.

Compared with other CNN based classification approaches, our approach has a main improvement:

(1) To reduce the CNN computation added a motion detection method based on background subtraction

.Only if moving objects appear, the following CNN computations will be implemented.

(2) To replace the hand-designed feature extractors or the slide window methods for ROI generation, we used an object detection method based on YOLO to generate fire regions directly.

(3) To avoid the false alarm problem, considered carefully and focused on the classification between fire images and fire-like images using CNN
The performance of our approach can meet the needs of real time fire detection on the precision and the speed. It will help detect fire every early stage, facilitate the emergency management and therefore significantly contribute to loss prevention.

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