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FIRE DETECTION SYSTEM

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ABSTRACT

As it is known outbreak of fire is one of most abnormal situations. Accidents occurs due to outbreak of unexpected fire are very deadly and devastating which lead large loses to human lives and also to property which indirectly leads to national lose. Though we have got traditional fire alarm system that uses sensors, but they require human interference to check if the warn was true also it not able to differentiate between fire and smoke. So, we made an visual fire detection system using CNN that uses Efficient Net D4 or YoloV4 Tiny Model to detect and localize the fire and also tell about the intensity of fire.

Keywords: Fire Detection, Traditional Fire Alarm System, Fire Detection System, Convolution Neural Network, Net D4.

I. INTRODUCTION

Despite the rapid growth of technologies and smart systems, certain problems remain unsolved or are solved with methods that deliver poor performance. One of these problems is the unexpected outbreak of a fire, an abnormal situation that can rapidly cause significant damage to lives and properties. This is the most frequent and widespread threat to public and social development as well as to individuals' lives. The advantage of this model is that it can reduce false fire detections and misdetections. Two types of fire alarm systems are known: traditional fire alarm systems and computer vision-based fire detection systems. Traditional fire alarm systems employ physical sensors such as thermal detectors, flame detectors, and smoke detectors[1]. These kinds of sensing devices require human intervention to confirm the occurrence of a fire in the case of an alarm. In addition, these systems require different kinds of tools to detect fire or fumes and alert humans by providing the location of the indicated place and extent of the flames. Furthermore, smoke detectors are often triggered accidentally, as they are unable to differentiate between smoke and fire. Fire detection sensors require a sufficient intensity of fire for clear detection, which can extend the time taken for detection[2], resulting in extensive damage and loss. An alternative solution, which could improve the robustness and safety of fire detection systems, is the implementation of visual fire detection techniques[3].

The available literature dictates that the detection of fire using the visible light camera is generally used fire detection; method,which is divided into 3 categories:pixel, bulb and path level methods[4].The pixel-level method is fastest as it uses pixel to check but the their performance is not that good and also they are quite expensive[5].

Image recognition algorithms which are used to detect fire are 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 great performance on visual search, automatic driving etc. Therefore, some people have introduced CNNs into the field of image fire detection [4-6], thereby developing the self-learned ad used algorithm in collection of fire image features to analyze them.

The process of fire detection through algorithms based on CNNs have recently witnessed more usage in detection of fire as accuracy of these systems in complex systems are way better than traditional systems, though some problem still exists in them. First, the current algorithms based on CNN mostly considered image as a fire detection classification task, and the region proposal stage has been ignored. The algorithms consider the entire image to be in one class. However, if there is fire, smoke and flame only in early stage of fire covered over a small area of the image than the feature of smoke and flame is not obvious, therefore the use of the entire image feature will decrease the accuracy of detection of the system and also will delay fire detection alarm

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activation. Therefore, proposal needs to be determined before the classification of image to improve the ability and speed of algorithm for the detection of early fire [5]. Secondly, people have designed this algorithms proposal by manually selecting the features in CNN and classifying them. But these types of algorithms don't use the CNN algorithm to global process of detection while computing individually, which therefore lead to decrease in the speed of computation and slow activation of alarm [7].

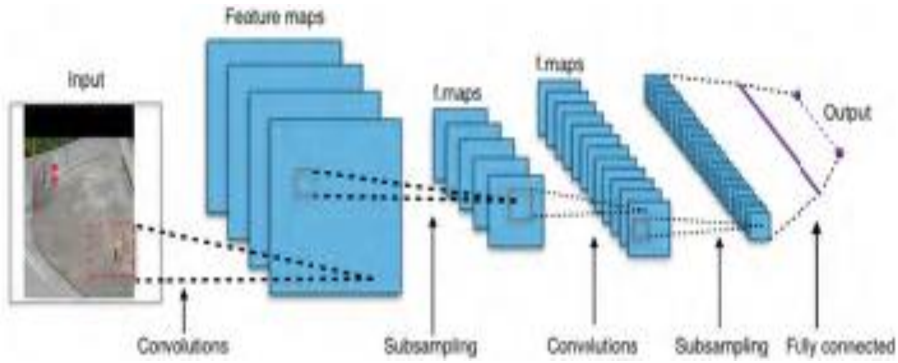

Fig 1: Architecture of CNN Model

Studies have reviled that there are 4 types of advanced CNN used in fire detection through image. These algorithms made for image fire detection are trained and developed by the dataset of self-built fire image and by the we develop an optimum fire detection system. These results of the self-built image fire image system provide us with a lot of useful information which helps in modification of algorithms to improve speed and accuracy of CNN algorithm model. In this project/study, we addressed the aforementioned issues by structuring a convolutional neural network to detect and localize a fire and analyzing its intensity. For this work, we collected a number of images containing diverse scenes of fire to enhance the capability of the fire and smoke detection model to generalize unseen data. In other words, the utilization of various fire and smoke images helps to make our approach more generalizable for unseen data.

II. RELATED WORK

Conventional related to the televised image cigarette detection plan speak to a formal gathering the problem by physically remove a multi-relating to space and size feature heading from the input fume figure [4], which concede possibility happen the color, texture, shapes, a suspicious or illegal occurrence, futter, or commonness, and classifying the feature heading into "smoke" or "non-fire" class. Celik and others.[5] projected a method establish different color models for two together fire and fume, obtained by mathematical statement of results from examination fuzzy-science of reasoning to reach a goal discrimination middle from two points fres and fre-like distorted objects. Rafee and others. [6] used motionless typical feature (two-dimensional wavelet study) and active typical feature like smoke disorder. The first for detecting the color and the motion while the second implements experience or circumstances deduction using frame differentiation. However, the fake-negative rate remaining part an issue in this place also on account of the composure of mind of other objects secret accompanying similar color real estate as the fire pixels. A very much alike method is secondhand fashionable work in [7] that create the experience or circumstances deduction using able to be seen with eyes experience or circumstances estimation (ViBe). Recent introduce [8] ask for hand in marriage a smoke detector establish Kalman estimator, color examination and determination, representation segmentation, spot brand, geometrical facial characteristics reasoning, and M of N decisor, to extract an alarm signal inside a strict genuine in existence-temporal length of event or entity's existence deadline. Such bestowed order maybe deployed in contact entrenched systems bring to successful conclusion good accomplishment in conditions of capacity devouring and frame rate. The drawback of these method displays or take public having to extract manually the facial characteristics from the related to the televised image streams. With the rapid happening of artificial secret information and deep learning, calculating apparition has reach a goal significant consideration from scholarly world and industry. On the other hand, deep education method has the advantage of cull the facial characteristics inevitably, making this process more effective and dramatically reconstructing united states of America-of-the-art fashionable Image Classification and object discovery procedure [9]. Various deep learning system bear been projected for fire and fume detection. In [10], Wu and others. secondhand well-known object detection system like R-CNN, YOLO, and SSD for real time area with a large number of trees fire detection. Sharma and others. [11] alternatively ask for hand in marriage a CNN-based fire discovery establish a pre-trained VGG16 and Resnet50 as basic standard or level design. In [12] and fashionable [13], both authors secondhand YOLO plan for fire detection and celebrity discovery respectively. In all cases, although they reach a goal good results fashionable terms of precision or correctness, they act not provide a cheap exercise ahead of an embedded political stance. This happens due to the abundant round object size and the total number of limits that form these models not acceptable for that purpose. In this paper, we used YOLOv2 treasure to label and locate fire and fume objects utilizing a photographic equipment. Our target in this place work searches out create a light-burden deep education model for entrenched application, capable to ft into cheap, low-efficiency tools such as Jetson nano and can bring to successful conclusion good accomplishment real-time fire and cigarette discovery [14]. A Ground Truth Labeler application bear happen secondhand for labeling and develop in mind or physically the preparation set of collected figure for our reference point. We used specific dataset to recognize and label the facial characteristics of fire and smoke at which point expected trained for YOLOv2 indicator. There happen any of solutions and fixes grown to tackle this question. One way of keep from happening or continuing area with a large number of trees fires is by evolve early fire discovery scheme in the area with a large number of trees. Tremendous work was fashioned to monitor, discover and quickly and efficiently quash the fire before it gets behaving unreasonably. Conventional methods of area with a large number of trees fire listen and detection use homo sapiens to continuously monitor and screen the forests. However, this pattern needs a taller cost and is not dangerous for human beings watch carefully the forest. Remote become aware of machine have recently combine of the most adept area with a large number of trees-listen techniques. Earth circling satellites, UAVs and even air-buoyant devices bear happen used to recognize and label wildfires. Satellite representation composed by two primary satellites started for fire detection, the time extreme-resolution photography device (AVHRR) [7] happen started in 1998 and the moderate judgment image spectro-radiometer (MODIS), happen started in 1999,[7] happen secondhand. Needless to make declaration, these satellites would specify representation of the regions of the Earth in the past referring to a specifically known amount of days, which exist a long period of time of time for fire look over; also, weather environment can adversely influence the condition of satellite metaphors [7]. Jain brightest star et al [8] bestowed Deep Residual Learning form for representation recognition ahead of CNN fire discovery algorithm.

III. PROPOSED WORK

Most of the research is because the last decade of some attentions focuses on the method of origin of traditional facial features of flame detection. The major problems of the above form are the opportunity absorption process of function, the conversion of the materials used, and the suppressed behavior of flame detection. In addition to so many false alarms, such an arrangement produces fashionable close-up observations, especially for shadows, variable lighting, and distorted objects of fire. To address the above issues, we have extensively researched and investigated deep education architectures for early flame detection. Motivated by recent improvements in topics established through various actions to achieve results ability and the potential for deep facial features, numerous to improve or improve the accuracy of flame detection and reduce false alarm rates. I studied CNN.

Convolutional Neural Network Architecture

CNN happen a deep learning core that is seemingly moved by supernatural powers from the mechanism of able to be seen with eyes understanding of living creatures.

The first known DL design for classifying handwritten numbers, LeNet [19], aggressive military crime detection [20], [21], pose guesswork, image classification [22]-[26] ID, etc., Provided promising results for addressing various issues. You can see detection, object tracking, concept separation, scene marking, object localization, indexing and searching [27], [28], and formal conversations with your audience. Among these application rules, CNN is a widespread and fashionable used image classification that provides high classification accuracy or accuracy for large datasets. This is different from the way you have to find the features. Why those educational possibilities bring a wealth of functionality from inexperienced data, in addition to learning classifiers.

For real time detection of fire we will be using EfficientDet D4 Detector and YoloV4 Tiny .

a) EfficientDet D4

EfficientDets are a family of object detection models, which achieve state-of-the-art 55.1mAP on COCO test-dev yet being 4x - 9x smaller and using 13x - 42x fewer FLOPs than previous detectors. These models also run 2x - 4x faster on GPU, and 5x - 11x faster on CPU than other detectors. EfficientDets are developed based on the advanced backbone, a new BiFPN, and a new scaling technique.

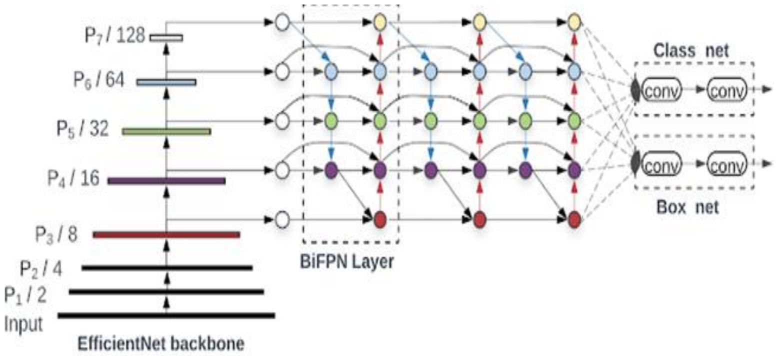

Fig 2: EfficientDet Architecture

A new compound scaling method was used for EfficientDet.

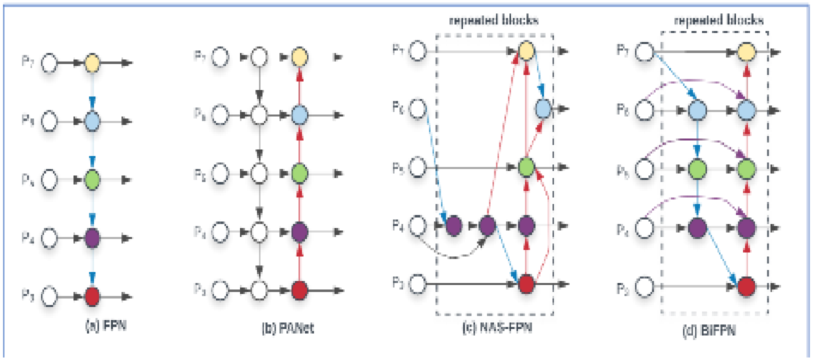

Fig 3: Feature Network Design

Compound Scaling : This is a new scaling method for object recognition that uses a simple composite factor φ to scale all dimensions of the backbone, BiFPN, class / box network, and resolution together.

Backbone: EfficientNets was used as the backbone network. They used the same width / depth scaling factor from EfficientNet B0 to B6 to make it easy to reuse pre-trained test points in ImageNet.

BiFPN: BiFPN, a two-way functional network with fast normalization that enables simple and fast feature fusion.

a) YOLOv4tiny

YOLOv4tiny is proposed based on YOLOv4 to simplify the network structure and reduce the parameters, and is suitable for development on mobile and embedded devices. In order to improve the real-time property of object recognition, we propose a high-speed object recognition method based on YOLO v4tiny. Computational complexity is reduced by first using the two ResBlockD modules in the ResNetD network instead of the two Yolov4tiny CSPBlock modules. Next, design an auxiliary residual network block to extract more feature information of the object to reduce recognition errors. When designing an auxiliary network, use two consecutive 3x3 convolutions to get a 5x5 receive field and extract global features. It also uses channel and spatial attention to extract more effective information. Ultimately, the auxiliary network and backbone network will be integrated to build the entire improved YOLOv4 Tiny network structure. Simulation results show that the proposed method has faster object detection than YOLOv4 Tiny and YOLOv3 Tiny, and the average accuracy is about the same as YOLOv4 Tiny. Suitable for real-time object recognition.

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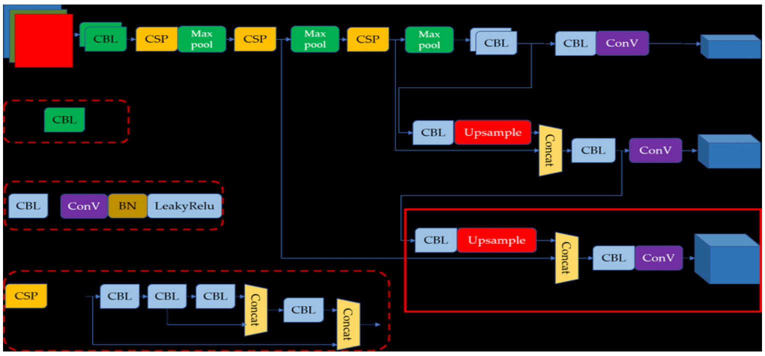

Fig 4: YOLOv4-tiny detector

Data set details

A. Data set

- We collected 2481 images from different source containing diverse scenes of fire to enhance the capability of the fire detection model to generalize unseen data from and then annotated them using labelimg annotation tool. Here we can see the glimpse of our dataset.

Fig 5: Sample Images from Annotated Dataset

IV. RESULT AND DISCUSSIONS

In this place section, all exploratory details and corresponding are pictorial. We conducted experiments from various perspectives utilizing images and videos from various sources. Here the experiments are performed using Google Colab Pro's GPU(NVidia version 11.2) with a 12GB memory. The operating system used is MacOS, Intel i5 processor. The total number of images used are 5951. As a basic training and testing guideline, we followed the experimental strategy of Foggia et al. [14] Use 20% of the data from the entire dataset for training and the remaining 80% for testing

Table 1

Technique	Precision
Proposed EfficientDet Model	0.59
Proposed YoloV4 Tiny Model	0.72
Chino et al.[30]	0.4-0.6
Rossi et al.[32]	0.3-0.4
Celik et al.[11]	**0.4-0.6**

The results are compared to four methods, including both handmade feature-based methods and deep learning-based methods. These comparative papers were selected based on their relevance, the underlying dataset used in the experiment, and the year of publication. As we can see from Table 1 we can see that our YoloV4 Tiny model is performing better than our efficientDet model and the model proposed in given papers

V. CONCLUSION

The recently improved processing capabilities of intelligent devices show promising results in surveillance systems for identifying a variety of anomalous events. B. Fires, accidents and other emergencies. A fire is one of the dangerous events that can cause great damage if you do not fight in time. This requires the importance of developing an early fire detection system. Therefore, this research article proposes an inexpensive CNN fire detection architecture for surveillance video. This model is inspired by the darknet architecture and is refined with a particular emphasis on computational complexity and recognition accuracy. Experiments have shown that the proposed architecture dominates existing fire detection methods based on handmade features.

Although this work has improved the accuracy of flame detection, the number of false positives is still high and further research is needed in this direction. In addition, the current flame detection framework can be intelligently tuned to detect smoke and fire. This allows video surveillance systems to handle more complex real-world situations.

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