Fire Detection System using Deep Learning

ASHWINI RENAKE[1], PRANJALI SHINDE[2], AND PAYAL KEDARE[3], KARANDE PRITI[4]

GUIDE NAME- DR. H.B. JADHAV, ATC , AHMEDNAGR, 414005.

Adsul's Technical Campus Chas , Nimblak By Pass Road, Ahmednagar, Maharashtra 414005

Abstract

YOLO achieved modern performance in categorization of images and other computer vision applications. Including them in fire detection devices will significantly improve detection accuracy, decreasing fire incidents and their effects on the natural world and society as a whole The main problem with founded fire detection technologies is their deployment in actual monitoring networks because to have significant data and computing inference needs. The total number of fires reported each year has risen because of human actions and a dry climate. Several ways of detection have been thoroughly examined. However, because of the significant memory and computing demands for inference, using CNN-algorithm fire detection techniques in actual observation networks is extremely difficult. Establishing a classification in the suggested plan.

Keyword: - *Fire detection, CNN, Deep learning,Yolov3 etc*

I. Introduction:

Because of anthropogenic causes and a dry climate, the number of reported forest fires has increased every year. Numerous detection techniques have been extensively researched and put into use in order to prevent the horrible calamity of fire. Due to their low cost and ease of installation, sensors form the foundation of the majority of traditional methods. These systems cannot be used outside since the environment can impact the burning process and the energy of the flame, which could result in false alarms. Given that closed circuit television (CCTV) surveillance systems are increasingly common in many public locations and can assist in capturing the fire scenes, it has been demonstrated that a visual-based approach to image or video processing is a more reliable method to identify fire. Various techniques have been investigated for the purpose of detecting fire from scenes of color-videos, with the major emphasis on the combination of static and dynamic features of fire, such as color information, texture, and motion orientation, etc. Color-based detection techniques, which heavily rely on threshold values, have a significant false alarm rate that can be reduced by identifying dynamic fire features from a video sequence of still images. In large-scale and difficult-to-reach areas like isolated and untamed forests, where the system's design and maintenance are challenging chores, those systems are still not useful.

II. Related Work:

Among the various computer-based approaches to detecting fire, we discovered that Artificial Neural Network, Deep Learning, Transfer Learning, and CNN were the most prominent. For a quick solution, the study [2] shows Artificial Neural Network-based techniques that use the Leven berg Maraquar dt training algorithm. The algorithm's accuracy ranged from 61% to 92%. The

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Two ways are presented in paper [4]. The first strategy is to use Transfer Learning to train on the data set and then fine tune it. The following method was to extract flame features, fuse them, then categorise them with a machine learning classifier. Xception, Inception V3, ResNet-50, and ImageNet were the transfer learning methods employed. The first method obtained an accuracy of up to 96%. The AUC of the second strategy, which included Xgboost and lightbgm, was 0.996. Transfer learning models significantly minimise the quantity of time needed to train our model. It necessitates a smaller data collection. Both approaches do not necessitate any domain knowledge. The Deep CNN technique was used in works [7, 8] to identify and localise fires. In both of these articles, the accuracy ranged from 90 to 97%. This method takes time, and training was carried out on an Nvidia GTX Titan X with 12 GB of on-board RAM. Traditional machine learning with feature extraction produced great accuracy and a low false positive rate, but it required extensive domain knowledge, such as colour model, colour space, patterns, and flame motion vectors. When an object changes, the models must be rebuilt to accommodate the new object. The traditional method of feature engineering [12] is manual. It entails handcrafting features incrementally utilising domain expertise, which is a time-consuming, labor-intensive, and error-prone approach. The resulting model is problem-specific and may not perform well with new data. This wasteful technique is improved by automated feature engineering ([3][5]), which extracts valuable and relevant features from data using a framework that can be applied to any challenge. It not only saves time, but also creates characteristics that may be interpreted and prevents data leaking. Instead of starting from beginning with transfer learning, we may start with a pre-trained model and fine-tune it as needed. These models can be easily imported from Keras. The usage of pre-trained models saves a significant amount of computational labour that would otherwise require high-end GPUs. Inception V3, and Inception-ResNet-V2 were discovered to be appropriate feature extraction techniques due to their promising outcomes. With transfer learning, instead of developing a model from scratch, we can start from a pre-trained model with necessary fine-tunings. These models can be imported directly from Keras. The use of pre-trained models saves a lot of computational work, which otherwise, would require high end GPU's. Inception V3, Inception-ResNet-V2 were found to be ideal algorithms for feature extraction as they showed promising results with high accuracy.

III. Open Issues

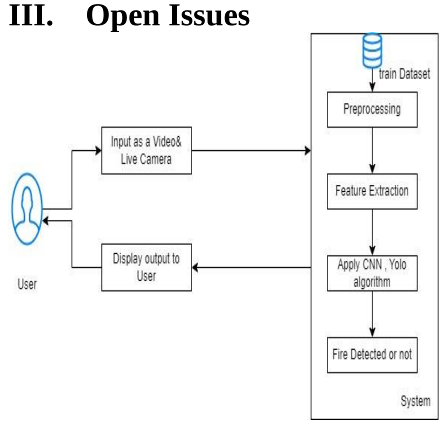

Fig 1. System Architecture

Module

•**Pre-processing-** Pre-processing relates to all modifications performed on raw data prior to delivering it to a machine learning or deep neural network algorithm. For example, training a convolutional neural network on raw photos will almost certainly result in poor classification performance.

•**Feature extraction-** YOLO extracts image attributes from input images, then other neural network classifies the image features. The network that extracts features makes use of the input image. The neural network uses the extracted feature signals for classification.

•**Classification-** The YOLO neural network is a type of deep learning neural network. YOLO represents a significant advancement in image recognition. They are most usually employed to analyse visual imagery and are extensively utilised in picture classification.

YOLOV3-

You Only Look Once, Version 3 (YOLOv3) is a real time object recognition system that can recognise certain objects in moving pictures, live feeds, or still images. The YOLO machine learning algorithm employs features that a deep convolutional neural network (CNN) has learned in order to locate an item. There are three iterations of the YOLO machine learning algorithm, with the 3rd iteration being an improved version of the first ML technique. Joseph Redmon and Ali Farhadi are credited with producing YOLO versions 1-3.

CONVOLUTIONAL NEURAL NETWORK-

A Convolutional Neural Network, also called a ConvNet is a Deep Learning technique that can take an input image, assign different elements and objects in the image importance (learnable weight and bias), and be capable of to differentiate between them. In comparison to other classification methods, a ConvNet requires significantly less pre-processing. Contrary to primitive techniques, where filters must be hand-engineered, ConvNets are capable of learning these filters and their properties.

IV. Proposed System

We Used the YOLOv3 algorithm in this project. YOLOv3 algorithm gives more accuracy.
fire detect for live camera by usingYOLOv3 algorithm. To detect fire, we used a pre-trained model. This algorithm supports live cameras and the CNN image dataset methodology. Run the system to send a mail message to the user if a fire is detected. This is our project proposed system.

Advantages are:

Quick fire detection, high accuracy, adaptable system setup, and the capacity to effectively identify flames in sizable areas and intricate building structures.

V. Result

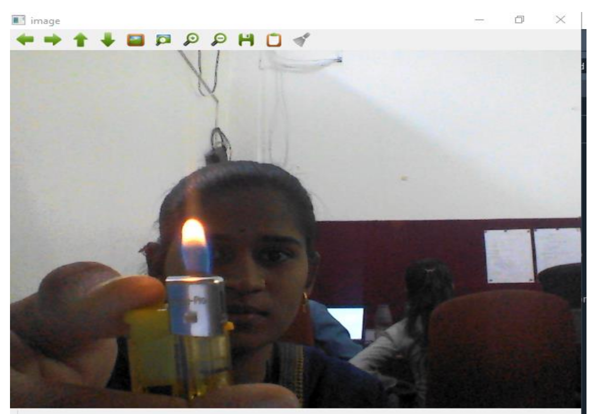

Fig 2. Fire Detection Page using Yolo

Fig 3 : Fire Detection Page using CNN

VI. Conclusion

Intelligent cameras can be used to detect many suspicious situations, such as car accidents, medical emergencies, and fires. The most dangerous of these irregular occurrences is fire, which, if not immediately controlled, can result in catastrophic disasters with losses to lives, the environment, and financial resources. As a result of CNNs and Yolov3, which have such great potential, we can detect fire from Live Camera or videos at an early stage. This article presents two distinct models for fire detection. Regarding the YOLOV3 Fire Detection Algorithm. Additionally, we use CNN's video algorithm. Because of the CNN model's accuracy, disaster management teams can use it to quickly handle fire situations and prevent serious losses.

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