Python Based Comparative Study of Video Based Fire Detection

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Abstract

Fire disasters are among the top 3 disasters that cause high amount of loss to both property and life. A system that is reliable, fast and can detect fire at an early stage is highly in demand. Fire Detection system can be used in CCTV video and doesn't require higher cost. These early and timely given warnings can save a lot of life and property. The commonly used methods are typically based on color and motion. There are many classifiers that can be used to differentiate between positive and non-positive pixels. In this opportunity we will create a fire detector system using different computer vision algorithms based on their accuracy, speed and other parameter and Internet of Things (IOT) in order to get the real-time detection results. Various Algorithm (such as HAAR, LBP, CNN) is used for the preprocessing of image, to detect the correct image of fire. As long as the camera will continue to monitor the conditions in the room. If there is a fire detected by the camera, then the fire image will be processed using Image Processing and the result is a data string sent to the server and forwarded to the user's smartphone (using the concept of IOT) as a warning (alert).

***Keywords—** HAAR Cascade, LBP, Adaboost, CNN, Fire detection System.*

I. INTRODUCTION

Fire detection based on video plays an important role in areas where conventional strategies, for example, sensor-based frameworks fall flat. Fire detection systems are mainly responsible for early warnings to user to take necessary step. These are for the most part liable for early alerts to client to make fundamental stride. Systems that are quick, and dependable are demonstrated to be life sparing and can help in decreasing death toll and property. Inability to identify these occurrences has caused a ton of harm and a solid framework is profoundly popular. It is extraordinarily required in places that are open or require a huge space and sensor-based frameworks can't be utilized as these are in compelling in open spaces. These systems are high in demand and can replace traditional system. These systems can also be managed centrally and can be accessed anywhere, through the use of IOT [13]. There are some other detection system available that are either not reliable or require high amount of processing power.Fire detection using recordings procured by reconnaissance cameras are exceptionally successful in the identification procedure.This system uses modern approaches to detect fire at an early stage and can be enhanced further for better and effective detection. The calculation utilized in fire discovery framework is accomplished by investigating a few highlights, for example, shading, shape, development and different other features [1].

A fast increment in fire mishaps and woodland fire brought about a more appeal for these frameworks and a framework dependent on PC vision is exceptionally compelling for these cases. Fire mishaps, for example, woodland fire and open territory fire are the normally happening calamities. There are different strategies dependent on various calculation for fire identification which uses colour and movement. Most of the present fire detection framework are inefficient as well as can cause bogus activating too. Present fire detection techniques dependent on physical sensors like temperature sensors, fire sensors. These sensor-based recognition frameworks are not truly solid for fire identification and can cause bogus activating[13]. For example, regularly there are instances of non-

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detection of fire because of part of smoke. It needs an adequate degree of fire inception for an unmistakable detection, which prompts a long identification postpone causing unsalvageable harms. Another option, which could prompt the improvement of strength and dependability in the present fire recognition frameworks, is the visual fire discovery approach along with rapid response to the incident using DL methods [5-8][12].

II. RELATED WORK

Fire mishaps are the most usually happening fiascos these days. So as to moderate the quantity of fire mishaps, an enormous number of strategies have been proposed for early fire location to diminish the harm brought about by such mishaps. Aside from the issue of early fire discovery, present alarm frameworks likewise end up being wasteful as far as the bogus activating of the caution frameworks. Present fire identification strategies are ordinarily founded on physical sensors like warm indicators, smoke alarms, and fire finders. Anyway, these sensor-based recognition frameworks are not truly solid for fire discovery. For example, regularly there are instances of bogus activating with smoke alarms, as it doesn't have the ability to separate among fire and smoke. Then again, the other two identification frameworks need an adequate degree of fire inception for an unmistakable location, which prompts a long recognition postpone causing unsalvageable harms. Another option, which could prompt the upgrade of heartiness and re-risk in the present fire discovery frameworks, is the visual fire location approach[9]. As a civility of the headway in different man-made brainpower fields, vision-based research fields like Image Processing and Computer Vision have seen a decent amount of productive advantages. Different profound learning (DL) models have had the option to easily outperform the human level exhibition in explicit PC vision applications like picture characterization. The visual-based fire recognition approach likewise has had the option to exploit these technological upgrades.The following graph showing the highest risk factor based on the survey in India during 2017.

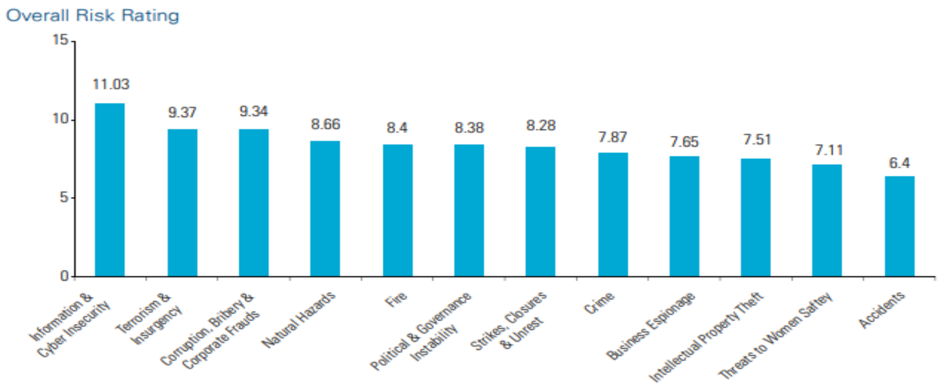

Fig. 1 Graph of the highest risk factor in India

Rezha Aditya et. al.Proposed in the paper Localization of White Blood Cell Images using Haar Cascade Classifiers tried to locate the white blood position in an image use the Haar Cascade Classifier Algorithm on this paper. And the result showed that the Haar Cascade Classifier can locating white blood cells with precision and recall values of 95per and74per respectively. With Haar Cascade Classifier Algorithm also able to differentiate the white blood cells from other objects that have resemble colour[15]. Yunyang Li in his paper discuss about a real-time eye gaze tracking system using Haar Cascade Classifier Algorithm.Yunyang Li and teams want to calculate the position of eye gaze with Haar Cascade Classifier Algorithm based on the rectangular features of human eye. The features of rectangular of human eye is adopted to match the coordinates of represented where an object is looking. And the results show that Haar Cascade Classifier Algorithm can validate the effectiveness of the system. [4].Recognizing fire is a significant issue, current innovation isindesperate need of a proper location framework that can diminish the harm caused because of countless fire mishaps occurring ordinary [7].At first, the specialists endeavoured to create carefully assembled systems for fire location by concentrating on the movement and shading properties of the

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fire location. One such work done by Thou-Ho et al. used colourproperty of fire and smoke for the genuine fire discovery.

In his paper Fire Detection Using CCTV with Image Processing Based Rasp-berry Pi by H Pranamurti and team discuss effectiveness of the HAAR cascade classifier in fire detection. They have used HAAR cascade for fire detection and implemented the system on raspberry pi. They have also used IOT for immediate alert system for the user [16].The use of LBP which is a texture based classifier was done in the paper Video-based Flame Detection using LBP-based Descriptor:Influences of Classifiers Variety on Detection Efficiency by Oleksii for flame detection by the authors. The efficiency of LBP for flame detection was tested. Other popular methods for flame detection was studied and compared with to get a betterpicture.Thevarious mathematical aspects of LBP was also presented in the paper[2]. The downside of manual feature extraction makes the hand designing assignment repetitive and wasteful, especially when the quantity of images in the dataset is high. Conversely, the DL-based methodologies have the upside of programmed include extraction, along these lines, making the procedure substantially more productive and solid than the traditional carefully assembled picture preparing strategies. These profound learning approaches require a great deal of substantial computational force, not just while preparing yet in addition when the prepared model is to be implemented to equipment for doing a particular task. On account of fire detection, the capability of the algorithm to be deployed on computationally substantial equipment like a PC machine is pointless since the unit should be comparable to a traditional fire detector, both as far as physical size and cost. [7,8].

Different profound learning approaches for fire detection have been proposed. Some proposed a CNN-based fire detection approach using Resnet50 and VGG16 as architectures. But both these methods require large disk size and are generally not well suited for outside fire detection using low computational power. The comparison table for the three algorithms discussed is given below.

Table I Comparison table for various algorithm

Method	**Background Model**	**Advantages**	**Disadvantages**
HAAR	HAAR uses integer value for detecting various features, which in turn gives high detection accuracy	High detection accuracy. Low false positive rate	Less accurate on diverse images. Limitation in difficult lightning conditions.
LBP	LBP compares central pixels with its neighbour and based on that do feature extraction	Computationally simple and fast. Robust to lightning changes.	Less accurate. High false positive rate.
CNN	CNN does both feature extraction and classification which is highly efficient and reliable	Faster and reliable algorithm. Very less false positive rate	High training time. Requires high processing environment

While the methods discussed can be used in variety of situations, but due to its less accurate nature in case of HAAR and LBP for diverse profile of fire dataset. We propose a CNN based model for fire detection in our system. The algorithm is not only effective and reliable in a diverse environment but can be made smaller in size by carefully tweaking the parameters to be able to run on low end devices.

III. ARCHITECTURE AND METHODOLOGY

The architectureproposed takes into account some of the anomalies of previous methods that are bulky and have issues with diverse dataset.The architecture mentioned in the block diagram examines various algorithm and at last the best among them is chosen to be implemented for the video based fire detection system. The proposed architecture takes the input data as video and based on the feature extraction and classification detects whether there is fire in the video or not. As soon as fire is detected an alert is triggered to the user which receives the alert of fire on smartphone using email. The email contains the location and the link to view the live feed of the fire accident. The user can than take necessary precaution to avoid major destructions,

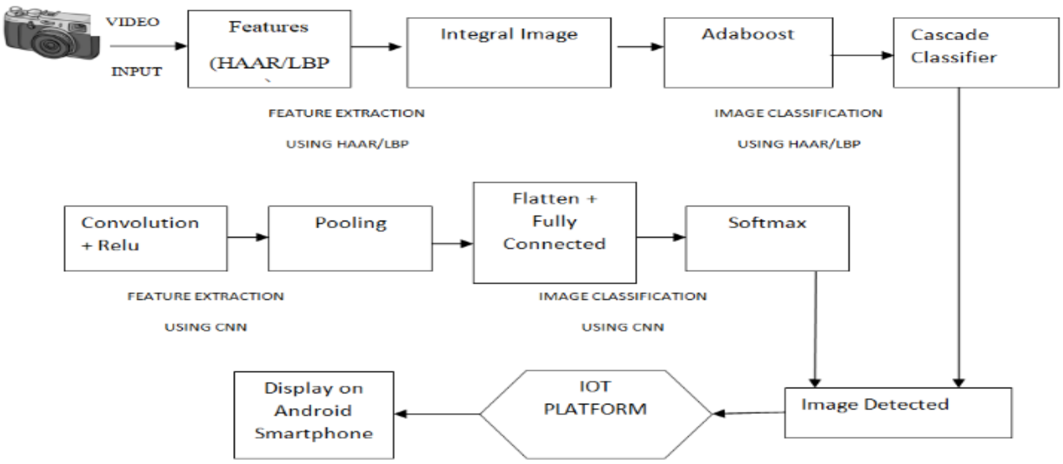

Fig. 2 Block diagram of the fire detection system

A. HAAR Cascade Classifier

One of the algorithm used is Haar Cascade Classifier, which is a strategy for identifying objects in a picture, and the technique for Haar Cascade Classifier is an item recognition technique created by Viola Jones. This strategy depends on Haar-like highlights, joined with the classifier course are reinforced. Haar-like highlights are highlights that are generally utilized in detection of items, offering fast extraction process and can speak to a lower goals picture [4]. This technique has been effectively applied in many article discovery. The classifier generally is prepared from a portion of the positive instances and negative instances, which have a similar size. The area is marked with 1 Classifier for rated similar to object or 0 to be assessed are not similar. After the training, the Classifier can be found all across the entire object with a region of the image. What's more, to recognize the objective region all the more precisely, the examining window size changed adaptively by Classifier. During the procedure of grouping, the model highlights the ideal square shape are chosen as per the items and the examining window [3].

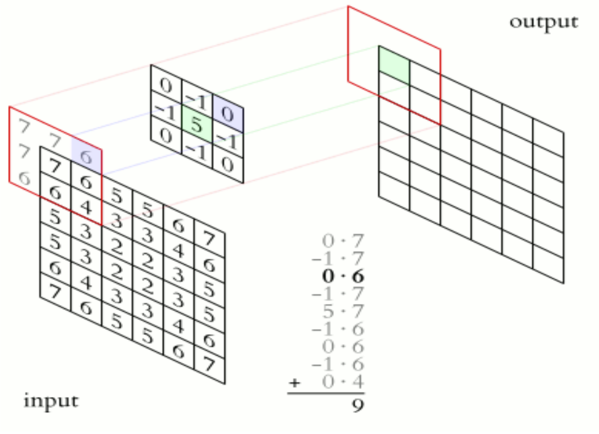

Fig. 3 Example to elaborate working of Haar Cascade

Cascade of classifier is used constructs a strong classifier as a linear combination of these weak classifiers.
Strong classifier = linear sum of weak classifiers

$$F(x) = \sum (\alpha_i * f_i(x)) \qquad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

here α_i are corresponding weights to each weak classifier $f_i(x)$

B. LBP Classifier with Adaboost

LBP was initially proposed for surface arrangement by T. Ojala et al. This administrator contrasts a focal pixel and its neighbours and, if the power of the pixel under investigation is smaller than the focal pixel of the window, it is doled out a zero, in any case the focal pixel is equivalent to one. Several variations of LBP have been proposed such as uniform LBP, an LBP invariant to rotation, an LBP uniform and invariant to rotation and an LBP that is not redundant. The uniform rotation invariant patterns describe basic structures such as flat areas, points, edges, curves, corners and end of lines, regardless of their orientation. Smoke texture changes constantly without following a definite pattern, therefore does not have a defined orientation and contrast, thus they can be discarded. This is the motivation behind utilizing non-repetitive LBP designs that consider indistinguishable spatial structures that are integral in their complexity [2].
LBPs compute a local representation of texture. This local representation is constructed by comparing each pixel with its surrounding neighbourhood of pixels. LBP looks at points surrounding a central point and tests whether the surrounding points are greater than or less than the central point (i.e. gives a binary result).
The first step in constructing the LBP texture descriptor is to convert the image to grayscale.
For each pixel in the grayscale image, we select a neighbourhood of size r surrounding the centre pixel. A LBP value is then calculated for this centre pixel and stored in the output 2D array with the same width and height as the input image.
To account for variable neighbourhood sizes, two parameters were introduced:
1. The number of points p in a circularly symmetric neighbourhood to consider (thus removing relying on a square neighbourhood).
2. The radius of the circle r, which allows us to account for different scales.

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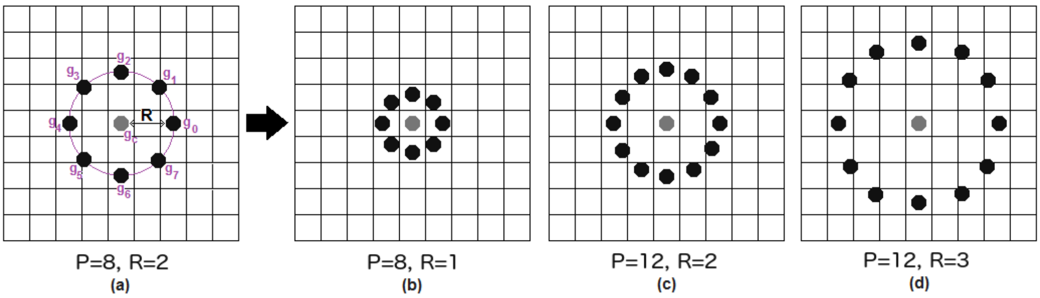

Fig. 4 Example of LBP working

here LBP code is given by Equation 1, where I_thresh is the chosen threshold value and I_n are the intensities of the surrounding window pixels with different values of n.

$$\text{LBP code} = \sum_{(\text{over } n)} \text{step\_fun}(I_n - I_{thresh}) \times 2^n \ , \quad \text{step\_fun}(x) = \{(1 \text{ if } x \geq 0,\ 0 \text{ if } x < 0)\}$$

….(2)

In this figure, we take the centre pixel (highlighted in red) and threshold it against its neighbours- 8 pixels. If the intensity of the centre pixel is greater-than-or-equal to its neighbour, then we set the value to 1; otherwise, we set it to 0. With 8 surrounding pixels, we have a total of 2 ^ 8 = 256 possible combinations of LBP codes. [11]

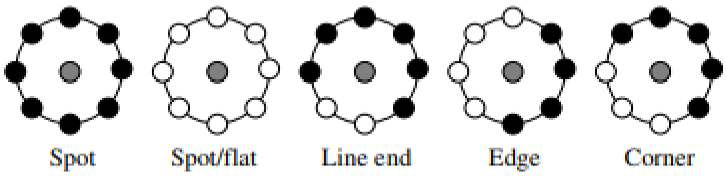

Fig. 5 Different texture primitives detected by the LBP

From here, we need to calculate the LBP value for the centre pixel. We can start from any neighbouring pixel and work our way clockwise or counter-clockwise, but our ordering must be kept consistent for all pixels in our image and all images in our dataset. Given a 3 x 3 neighbourhood, we thus have 8 neighbours that we must perform a binary test on. The results of this binary test are stored in an 8-bit array, which we then convert to decimal

C. CNN Based Model

The past profound learning based fire identification approaches only followed the process of calibrating distinctive CNNs like VGG16, SqueezeNet, GoogleNet,Resnet, and MobileNetV2. One significant downside with such methodology is they are cumbersome CNNs and their last on-circle size of the prepared model and number of layers is excessively huge, in this way forestalling these prepared models to run easily at an adequate edge rate on minimal effort equipment like a Raspberry Pi for constant fire recognition. Additionally, it is very clear that the accentuation of the prepared model to run at a decent casing rate on minimal effort equipment like Raspberry Pi is especially legitimate, since the ultimate objective of every one of these methodologies is execution for certifiable applications,[6] i.e., to be changed into different fire detection units introduced in the necessary condition like a shopping centre, a habitation, lodging, and so on. In this manner, there is the need to utilize financially accessible ease equipment, which is monetarily attainable dissimilar to a significant expense broad computational machine which is worthless in certifiable fire discovery applications. The framework can be utilized in low end gadgets, as the calculation doesn't require a great deal of memory. It doesn't require nearness to the influenced zone and can distinguish fire in open spaces and large lobbies, as it doesn't require closeness [7].

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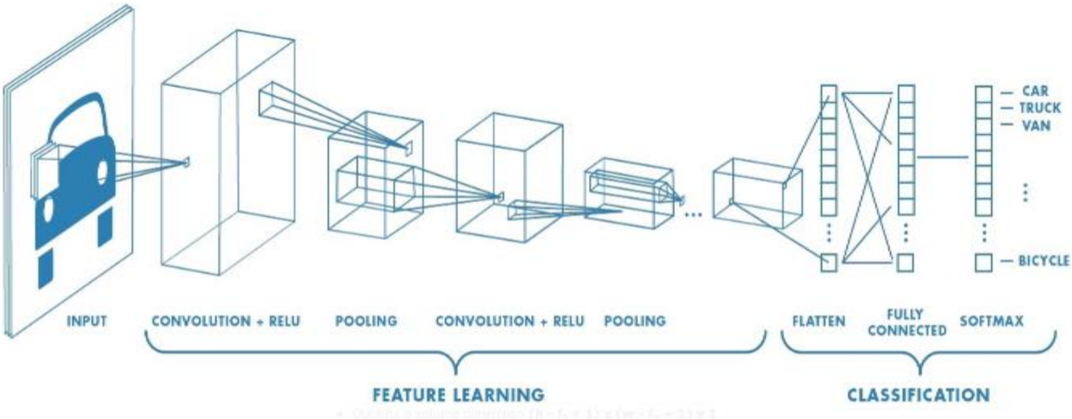

Fig. 6 CNN model basic architecture

The proposed neural network has three convolution layers and three dense layers in addition with pooling, dropout and
'Softmax' output layer. There are three convolution layers along with pooling and dropout layer. The activation function used is Rectified Linear Unit (Relu),Softmax is also used as the activation function for the last layer. The first layer is a convolution layer, which takes a coloured input image of size (64×64). The kernel size chosen is (3, 3) and is fixed. In each of the two subsequent convolution layers, we doublethe input features keeping the kernel size constant. This isfollowed by a flatten layer and 2 dense layers. The final layer is a dense layer, acting as the output prediction layer.[8][14]

IV. RESULT AND DISCUSSION

The below result is for the HAAR based detection system which as compared can successfully detects the flame but fails when used with larger fire footage. This shortcoming is resolved by the CNN based model. The CNN based model can detect the fire in any situation with higher accuracy

Fig.7 a) HAAR Based fire detection Fig.7 b) CNN Based fire detection

The fig.7 shows the working of the CNN based approach for the fire detection system. The system predicts if there is fire in the video footage or not based on the trained model. As shown in the below fig. when there is no fire in the video footage the probability is very less which can be neglected based on threshold probability for actual fire detection.The system at present is based on CNNarchitecture and is able to detect fire in video footage the frame rate is alsohigh.
The performance obtained from these methods are summarised below based on three parameters of accuracy, false positive and false negative detection.

Table II Accuracy of CNN based Model

Metrices	CNN Based Model
Accuracy	91.3%
False Positive	7.6%
False Negative	1.1%

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There accuracy of other two methods where not so encouraging when used with such a diverse dataset as in CNN based model, The number of false positive and false negative where a lot higher than the CNN based model. The Haar and LBP classifiers worked well when used with smaller and less noisy video footage, but lacks accuracy when tested on more real footage. Thus, CNN based model performed exceptionally well as opposed to other methods.

V. CONCLUSION

This paper proposes a vision-based fire detection framework using CNN. Analysis of different classifier is done and their effectiveness and precision is considered for actualizing the framework. The CNN based model after fine tuning is an exceptionally lightweight neural system prepared on a very diverse dataset which out performs the other two algorithms in diverse environment. A definitive point of the total work is to build up a web of things (IOT) fire detection unit that can adequately supplant the current physical sensor based fire finders and furthermore can lessen the related issues of bogus and delayed activating with such fire locators. The performance obtained by the model on a standard fire dataset and an independent test dataset regarding exactness, accuracy, review is empowering. Also, the IOT usefulness permits the identification unit to give constant visual feedback and fire alert if there should arise an occurrence of fire crises to the client. In our future work, oneintends to improve the presentation of the model on even a progressively differing dataset.

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