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DYNAMIC BEHAVIOR BASED FIRE RECOGNITION USING TRANSFER LEARNING

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Abstract: Artificial intelligence has its demand in almost every possible field, such as, medical, agriculture, military and so on. In depth, it is used to detect cancerous cells, lane detection, natural language processing, number plate recognition, and also in identification of fire. Fire has its own set of behavioral traits. Its static behavior includes color, texture, brightness and edge characteristics for identification. The movement characteristics and shape will fluctuates incessantly constitute the dynamic behavior of fire. The proposed approach presents an effective way of recognizing fire. It consists of two stages namely, the dynamic behavior extraction and static behavior extraction followed by classification. The pre-trained neural network is used for classification, which is termed as transfer learning. The first stage aids in ruling out all the unnecessary characteristics. The output of the first stage goes through the second stage, where all its static features are studied to put it under the correct category of classification.

***Index Terms* - Dynamic, Static, Feature Extraction, Transfer learning.**

I. INTRODUCTION

Natural occurrences are those which are chosen by the nature. During which, none of the life is spared. Currently the point to consider is fire. As, the fire occurs naturally, recognizing it is extremely vital. Natural disasters caused by humans or accidents; fire occurrs due to these disasters, is the reason for the loss of people's lives, their properties and belongings, and not to forget, the loss of the trees, crops caused by it. Almost every year, there will be news related to fire causing havoc in the lives of many, and the huge amount of devastation originated from it. Forest fires are not less common. These forest fires caused naturally or due to the cruel barbaric people for their own selfish reasons such as quarrels between neighborhood regions, in the intention of acquiring properties and so on. It cannot be taken as an excuse and must be given utmost attention and aid. It is the responsibility of every person to protect the nature. Though, none of the occurrences are in complete control of human beings, we can definitely manage to at-least prevent the further damage caused by it, by detecting it at the earliest. The proposed method of fire detection is a small step towards facilitating everyone by detecting the right fire scene, and by providing accuracy. Dynamicity is a very unique behavioral trait of flame. Due to which, its intensity levels keep fluctuating incessantly from one time to another.

II. LITERATURE SURVEY

P Foggia et al., [1] uses a competent framework to come up with a bundle of rules, based on characteristics of fire, such as color of fire, its form and its movement, which thereby provided greater precision, but simultaneously was affected in terms of greater false alarm rate. Kosmas et al., [2] constructed a Support Vector Machine classifier for detection of fire, based on movement characteristics, tone characteristics, sparkle characteristics, and color prospect characteristics. Toreyin et al., [3] conducted an in depth study on distinction of fire and victoriously utilized a hidden Markov model and performed fire recognition on video real-time. Deep learning consists of extraction top-level abstract features from data with the help of non-linear expressions and by forming mathematical models to obtain refines classification and precision of recognition of fire; therefore, it happened to be a famous research zone in the community of machine intelligence. Recently, many neural network models were initiated, namely Recurrent Neural Networks (RNN). They definitely are unique in their way; also have their demerits [4].

Frizzi et al., [5] propounded a method which utilizes o CNN for detection of fire along with smoke recognition and hence, conducted a test of it on footage. K Muhammad [6] advanced the study and initiated a system which merges 5G network conveyance for fire recognition in unpredictable regions. Seebam rungsat et al., initiated a rule which merged YCbCr and HSV. The arrangement prefers additional color space transformation than using one color space system. It indicates the utilization of static properties of the flame. The model is not that steady enough [7]. Foggia et al., propounded an innovative movement recognition arrangement which has its basis of the chaotic behavior of the flame [8]. Dimitropoulos et al., [9] utilized different sorts of flame properties for appropriate judgment and bagged a pretty commendable performance. An ultra spectral camera is used to get rid of the limitations of RGB two versatile Computational Intelligence and Neuroscience cameras that have inability to find the difference amongst flame and casual light origin, like an LED.

III. PROPOSED MODEL

The proposed work uses the combination of the dynamic characteristics of fire and the static characteristics of fire. Fire, as we know, has both static and dynamic characteristics. Static characteristics consist of information namely gloss, color, texture and edges. Dynamic characteristics consist of flicker and movement characteristics. To proceed further with this, HSV color space is applied to each image frame. This will filter out the other objects, which do not fall in the range of color related to flame or flame-like objects. So, this is called as the first filter stage. Figure 1 shows the block diagram of the proposed work.

A. Process of Extraction of Dynamic Features

a) *Motion Detection:* Using a technique called background subtraction, motion characteristics are extracted from the input sample video. These attributes are known as the Flame Suspect Region. This is the second filter stage, which picks out only the incessant moving objects and showcases it on the frame.

b) *Flicker Detection:* Due to the air flow and ignition features, incessant change occurs in the structure of the fire. These changes result in the flickering of the fire. Hence, they are known as flicker characteristics. This is an important stage as it decides partially whether the particular frame falls in the range of suspect. The contours of every object in each frame are acquired. Firstly, in this stage, the very first frame is not put into finding contours, rather, a matrix holding the intensity of every pixel of the frame, is found. An accumulator in the form of an array, that has the dimension of the frame, is used to keep track of the fluctuations in the levels. And, a frame-fire-pixel-counter is a list, is used to keep trace of the number of the suspected pixels, having its indices for each video frame. For every contour of the second frame, at the x and y point, intensity is found and is compared with the first frame's intensity at this point. If the value is much more intense than the previous frame's, then accumulator's value at that particular point goes high by 'one', and this is termed as a fluctuation in the levels, hence the frame-fire-pixel-counter is hiked by 'one', indicating the point as a suspicion, else the accumulator at the point goes high by 'zero'. This is known as the frequenter step. At the end of second frame, we are left with a list of intensities obtained at the contours of regard of the frame. The points are held as the standard points at which intensities of the next frame are calculated as, well. These new values are compared with the previous list of intensities, and the frequenter step is performed. The lists of intensities are replaced with the newer ones. If at all there are new points, specifically, co-ordinates or pixels, in a frame, these are added to the list to pixels. The ratio of difference of amount of fire points between two frames with the number of points in the current frame is found. If it is greater than a particular value, the frame is considered to be a 'frame of suspicion'. The rest of the frames in the sample video, go through the same procedure. But, even before we can get to the end of the video, if the frame of suspicion is attained, then we directly move on the static feature finder stage, to confirm whether the frame is confirmed of having a flame behavior or not.

B. Process of Extraction of Deep Static Features of Fire

This stage is also termed as classification. An important method called transfer learning is used here. In short, a previously trained model like MobileNetV2 is taken. Only the last layer, known prominently as the classification layer and is retrained by utilizing a bulk of images for classes named as fire, fire-act, fire-candle, non-fire. The rest of the model freezes, through setting the parameters as 'untrainable'.

IV. EXPERIMENTAL SETUP

A. Pre-processing Block: This block plays a vital role in performing operations on an image prior to its usage in the other important stages of the system. As we know, some of the most common form of pre-processing functions in images are reading the image where it is converted into an array, resizing the image- as required by the system's process, segmentation- used in problems involving location of objects, morphology- smoothing edges, noise suppression - to improve the quality of the image, warping of images, rotation of images, conversion of color spaces. Here, in the proposed system, the image is read and converted into an HSV color space.

B. Dynamic Feature Extractor: HSV color space enables better background subtraction. Image is further dilated to fills holes. The crucial part now comes into action. The very first frame is used to look up to its intensities. These intensities are stored in the form of a matrix. From then second frame, the contours of dilated image are found. Pixel list, intensity list, accumulator (counter), fire-pixel holder are created. The intensity of the current image is compared with the previous image. If the difference between current intensity and previous frame's intensity at the pixel is found to be greater than a set threshold, accumulator is increased by 1, and thereby, this indicates that the pixel is suspected to be a fire pixel, and hence current frame's fire pixel holder at that pixel co-ordinate is incremented by 1. This procedure is performed between the current frame and the previous frame for all the pixels of the pixel list. Once done, the ratio of the difference number of fire pixels between the two frames with the number of fire pixels in the current frame is calculated. If this value approaches 0, it indicates there is no much fluctuations in intensities at two different times. But, if this ratio approaches 1, it means there are fluctuations in the intensities at two different times. The current frame is now suspected to be having a region of fire.

C. Pre-trained Model

A pre-trained model, MobileNetV2, is chosen. Its bottom layers are frozen in order to avoid re-training of the bottom layers. This is because, the model MobileNetV2 is trained over more than 10,000 images of different classes of images, such as sky, animals, furniture, flowers, and so on. Weights that the model has learnt during its training period are of importance. To avoid losing the weights and other parameters that it has already learnt, the model's bottom layers are freeze completely.

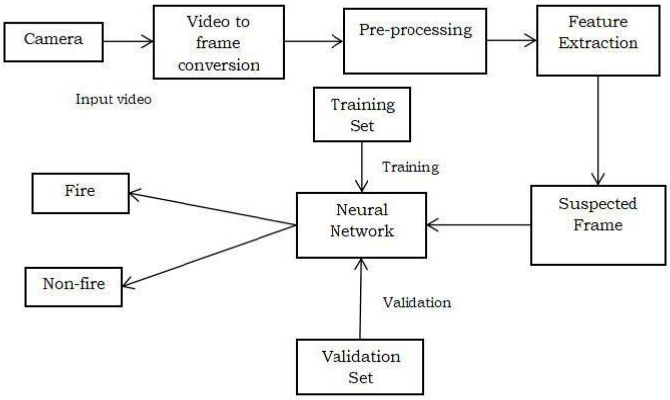

Fig.1 Block Diagram

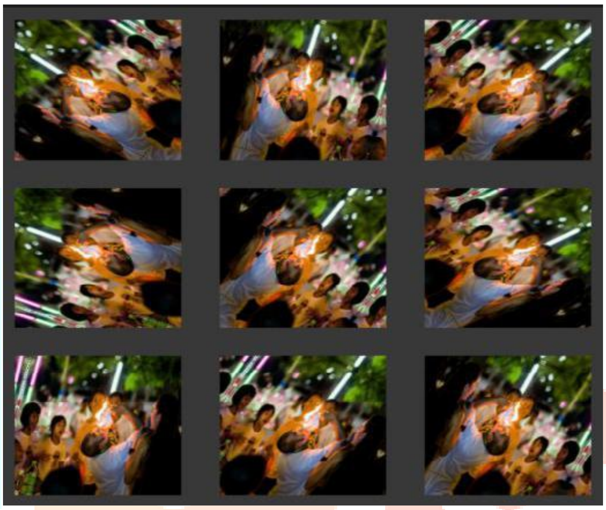

Fig. 2 Data Augmentation

The functions for the same are available in the Tensorflow library. Since, the number of classes in our problem is 4, only the top layer of the model, the classification layer is re-trained on the dataset containing the four classes namely, ‘fire’, ‘non-fire’, ‘fire-act’, ‘fire-candle’. Four classes are provided to train the model, so that it distinguishes between the images and classifies them even better. This model is saved prior to the dynamic feature extraction stage. The current frame of suspect which is obtained in the dynamic feature extraction stage, is sent to the saved model. The model extracts the deep static features of the fire internally, and based on the images it was trained, it classifies the current frame into either of the four classes.

D. Database

Around 4000 images were considered as training set. Data augmentation was performed such as rotation, cropping, mirroring, were performed on these images to increase the number of training images. So the total number of training images was around 6000. An approximate of 2000 images were augmented and given as validation set to validate the model. Around ten percent of it forms the test set. Data augmentation is also performed in order to make the model understand the data better. Figure 2 depicts the samples of data augmentation process.

V. RESULTS AND DISCUSSION

The static feature extraction - classification is vital to be trained well. The feature extraction of the model is freezed, so that it is not mistakenly trained. This is because the model has to remember the weights learnt by it when it was trained earlier over a different dataset. Table 1 shows the accuracy of training and validation for case 1. The number of epochs used here is 10, and the batch size is 16. The results are computed for two cases of training and validation ratio of images.

Case1: Figure 3 depicts the Graph of Training versus Validation Accuracy and Figure 4 shows the graph of training with validation loss. The classifier alone, of the pre-trained MobileNetV2 model, has been trained over 6228 images which belong to 3 classes, and, has been validated over 2378 images which belong to 3 classes. The training accuracy is 98.72% and validation accuracy is 96.10% .

Case 2: Figure 5 depicts the Graph of Training with Validation Accuracy and Figure 6 shows the graph of training with validation loss. The classifier alone, of the pre-trained MobileNetV2 model, has been trained over 6602 images which belong to 3 classes, and, has been validated over 2385 images which belong to 3 classes. The training accuracy is 97.41% and validation accuracy is 99.45%. Figure 7 depicts the classification results of different types of images.

Table 1. Training and Validation Loss with accuracy (Case1)

Number of Epochs	Training Loss (%)	Training Accuracy (%)	Validation Loss (%)	Validation Accuracy (%)
1	19.50	93.23	38.26	87.42
2	07.55	97.52	28.27	91.45
3	06.32	97.97	9.89	90.06
4	05.54	98.13	17.94	91.91
5	05.26	98.29	10.86	94.63
6	04.97	98.42	06.03	97.19
7	05.04	98.16	05.51	97.19
8	04.54	98.59	09.52	95.89
9	04.46	98.55	10.14	95.14
10	04.00	98.72	07.46	96.10

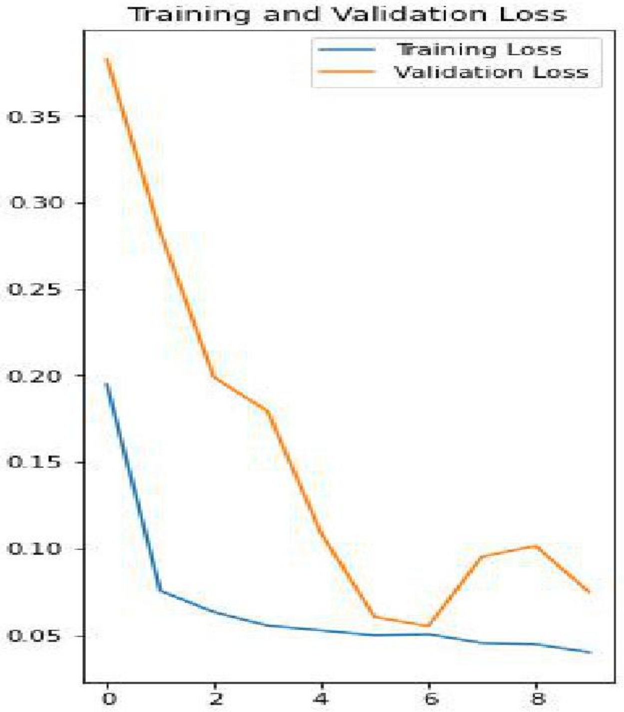

Fig.4 Graph showing Training versus Validation Loss (Case1)

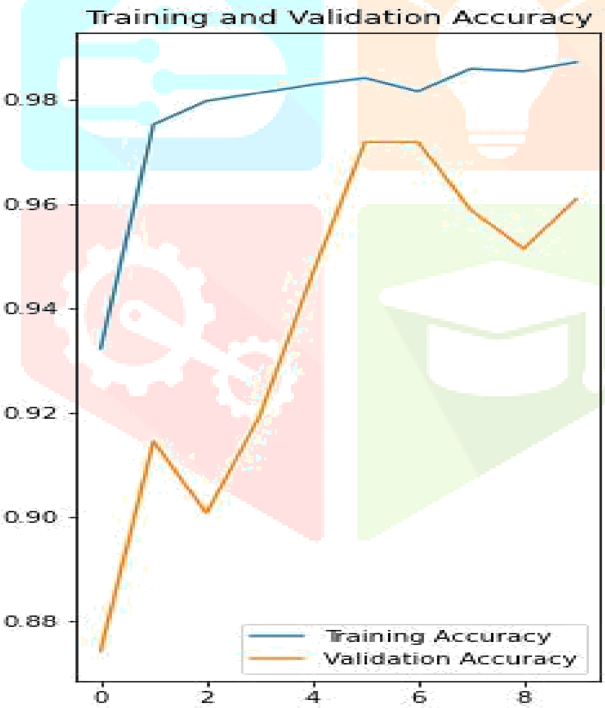

Fig.3 Graph showing Training versus Validation Accuracy (Case2)

Table2. Training Loss and accuracy along with Validation (Case2)

Number of Epochs	Training Loss (%)	Training Accuracy (%)	Validation Loss (%)	Validation Accuracy (%)
1	18.59	93.40	15.73	93.12
2	10.28	96.26	06.20	97.27
3	09.06	96.88	09.12	95.18
4	08.10	96.96	04.97	98.66
5	07.28	97.35	05.17	97.99
6	06.94	97.49	03.63	98.70
7	06.66	97.41	03.92	98.66
8	06.79	97.43	02.56	99.41
9	06.13	97.71	06.66	97.53
10	05.97	97.91	01.65	99.45

Fig.5 Graph showing Training and Validation Accuracy (Case2)

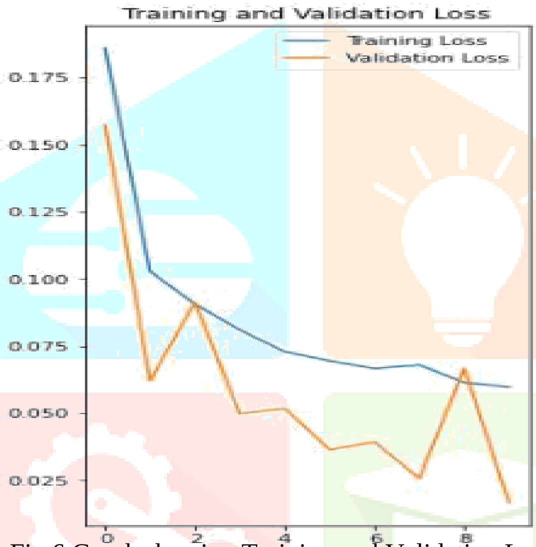

Fig.6 Graph showing Training and Validation Loss (Case2)

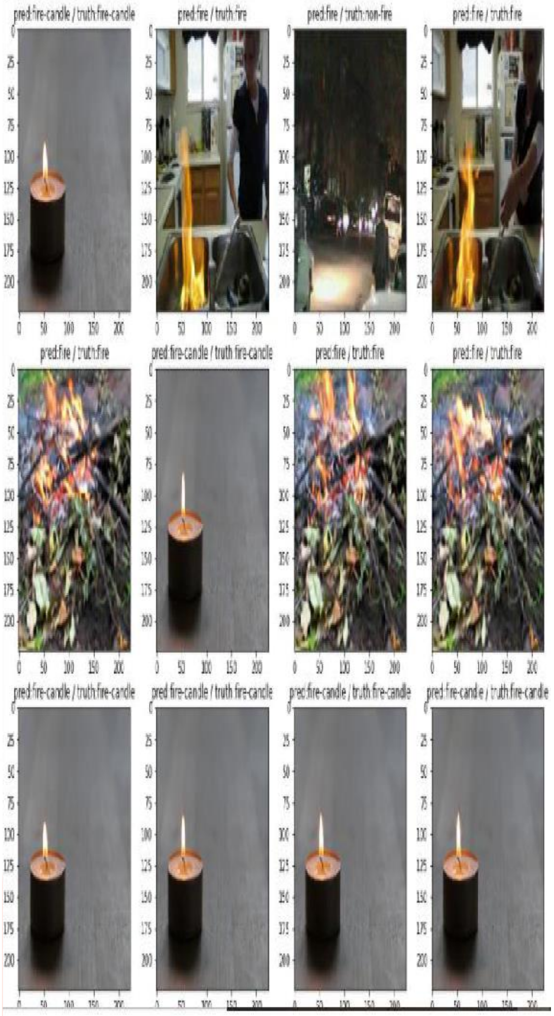

Fig. 7 Classification of images

VI. CONCLUSION

The transfer learning used in this work helps in efficient classification of fire, and also helps in detecting the fire scenes almost accurately. The network was trained well with good number of images for each class. The initial stage, which is extraction process of dynamicity of the flame, helped in finding out if ongoing video of a location has any region that functions like a flame. It helped in filtering out the non-vital traits stage by stage. And finally, as the neural network was trained before-hand, the suspected frame was passed on to the network for further confirmation. Further, advanced study can be performed to find the percentage of outspread of fire.

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