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Autoadaptive Flame Detection and Classification Using Deep Learning of FastFlameNet CNN

S Sruthi[1*] and Dr. B Anuradha[2]
[1]*Department of ECE, SVU College of Engineering, SV University, Tirupati, ssruthidtb@gmail.com*
[2]*Professor, Department of ECE, SVU College of Engineering, SV University, Tirupati, anubhuma@yahoo.com*

*__Correspondence:__ S Sruthi; ssruthidtb@gmail.com

ABSTRACT- Image processing technologies in the domain of pattern recognition have many successful researches and implementations. In that sequence, earlier detection of fire from the video footage of the surveillance cameras is an interesting and promising technique that serves mankind and nature as well. The traditional and existing methods of fire detection in the video frames are advantageous in industry-based applications. But whereas these techniques are applied to detect forest fire in a wider area, they have their limitations of inadequate output due to interferences caused by the sunlight and other natural attributes. To improve the detection efficiency using optical flow algorithms and to estimate the direction of the flame, a novel flame detection technique from the video frames using Optimal flow algorithm and the estimation of the fire flow direction using the Deep learning CNN FastFlameNet algorithm is explained in detail in this article. The performance of the proposed architecture is measured using the performance indices like Accuracy, precision, recall, F-Measure. It was estimated that about 97% of the performance accuracy was obtained from the proposed framework.

Keywords: Flame detection, Fire segmentation, CNN, Classification, Optical flow.

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1. INTRODUCTION

An unexpected and highly dangerous disaster that causes fatal damage and ecological unbalance is forest fire. Forest fire is a common and usual mis-happening that sabotages most of the forest area which is the most important asset of the ecology and environment that provides accommodation for many living creatures. Forest fire directly destroys many lives including the human population that abode near the forests and animals that live in the forests. Despite forest animals, water bodies and aquatic animals are also exposed to life threatening hazards. There were several records across the world about the forest fire that gave a big hit to the corresponding nation's economic status. In 2018, massive fires caused in the forests of California destroyed more than 766 thousand hectares of trees and animals. This was the world's largest ever forest fire in history [1]. The countries like Vietnam and Nepal where the major portions are covered by trees and forests are vulnerable to the frequent forest fires. India, where almost $1/5^{th}$ of the land was covered with forest, was known for its biodiversity reserves. Considering the largest fire accident in Indian forest it may directly affect the population surrounding the forest area and the environmental damages indirectly affects the Nation's economic condition considerably.

As the forest areas are very big to monitor manually each and every zone it is highly impossible to detect the fire in the starting stage and alarm the respective officials. Round-the-clock video monitoring of the fire situation replaces patrolling forests by a large number of inspectors and rangers. Now it is easy to detect the fire at the ignition stage, to pinpoint the place of its origin and then to coordinate the actions of various departments in the fight against the fire using dispatcher console.

Missed detection of the forest fire may lead to the most dreadful destruction. Hence an effective surveillance technique should be proposed or developed to identify the forest fire in its starting phase and should take respective actions to suppress them in the earlier period. This article explains about one such method where the artificial Intelligence algorithm was designed and the performance estimation is done against its performance parameters.

2. EXISTING SYSTEMS

The conventional fire detection systems are built with the sensor sensing technologies. But the external interferences due to the nature and manmade factors set limitations for the sensor performance. Also, the maximum performance from the sensors is obtained only when considerable input is given to them. The initial phase has no sufficient parameters required for the sensor to affect its performance and fails to detect the earlier fire. To overcome this problem an alternate technology is proposed which involves the use of image processing technology in the fire detection from the closed-circuit cameras and surveillance cameras.

The use of image processing techniques has many advantages like low installation expenses, real time data extraction, The detection of the fire in the image or video is easier than the fire detection through smoke alarms. Since the cameras are always placed at a considerable altitude the damage to the device or the digital camera is always less. The use of the updated algorithm every time enhances the performance of the fire detection system. Several techniques were used in the fire detection using image possessing methodology.

In flame detection using video, Markov algorithm was used. In this technique the flame and pattern of flame with similar shape and colours, Markov's model is used for the identification. The distinguishing is done by the flickering process and flame-coloured objects in the video [2]. Similarly, the flame detection in the video is done based on the contour and colour features in the RGB and HSI colour space. When using the colour spaces the Chan-Vese algorithm is employed to extract the attributes in the flame contour areas. The model is based on an energy minimization problem, which can be reformulated in the level set formulation, leading to an easier way to solve the problem. Chan-Vese algorithm relies on global properties (intensities, region areas), rather than just taking into account local properties, such as gradients. One of the main advantages of this approach is better robustness for noise. But the algorithm is sometimes quite slow, especially when dealing with large images. It can pose a problem for real time applications, such as video sequences, and an efficient implementation is very important. The attributes against the motion of the contours are analysed to find the displacement and vibration parameters of the flames [3]. An advanced technique of the frame difference model to distinguish the flame and background frames was proposed to identify the flames. The distinguishing of the frames was done based on the high brightness values [4]. However, all these methods have disadvantages like difficulties in distinguishing, Deviation of the results due to the colour adaptation of the frames, the output of the filters are always based on the pixel rate of the pictures not on the frame rate of the video. False identification of the flames occurs due to the existence of the noise, occlusions and change of the angle. Hence an effective and efficient method for identification of the flames in the image or video is proposed in this study.

3. PROPOSED SYSTEM BLOCK DIAGRAM

In the proposed system a set of the attributes based on the motion estimators was identified. Fire's turbulent, fast motion can be exploited over other objects' structured, rigid motion, taking advantage of the differences between them. The basic concept is to distinguish between the unstable rapid motions of the flames and the rigid and organized motion of the other objects. The existing methods have no idea how to present the attributes of the flame motion like turbulence, random intensity across the flame structure Hence in this proposed model two new algorithms are specially customized for the identification of flames in the image or the video. Dynamic fires are detected using the optimal models and data driven modelling schemes were employed to detect the saturated flames.

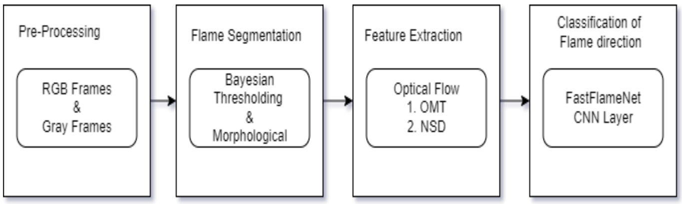

Figure 1: Block diagram of the proposed system

The distinguishing between the flame motion and the movement of the other objects were done using the attributes like flow magnitude and direction components. After the successful prediction of the flames using an optical flow algorithm, a deep learning based Fast flame net framework is proposed for the prediction of the fire movement direction.

The block diagram for the proposed methodology was given in *figure 1*. The block diagram clearly exhibits three different works done in the proposed framework. Initially the signal is pre-processed for obtaining the frames in RGB format and in scalar format. Then the feature extraction is done to obtain the feature vector which holds the information. Then these vectors are subjected to classification to identify the flame frames and predict its direction of movement using the deep learning algorithm.

3.1 Pre-processing of the Signal

This step is needed to estimate the attributes of the physical device recording the images or the video. For real-time surveillance video processing, first, we need to convert the video to a number of frames which depends on the frame rate of the video recording device. This MxNx3 sized RGB frame is converted to MxNx1 Gray space model to perform the segmentation in a single-color space dimension, where M and N are frame height and width respectively. Thus, this is a basic step much needed to compensate for the variability of the source device like the hardware specification of the camera, illumination properties, etc.

3.2 Flame Segmentation

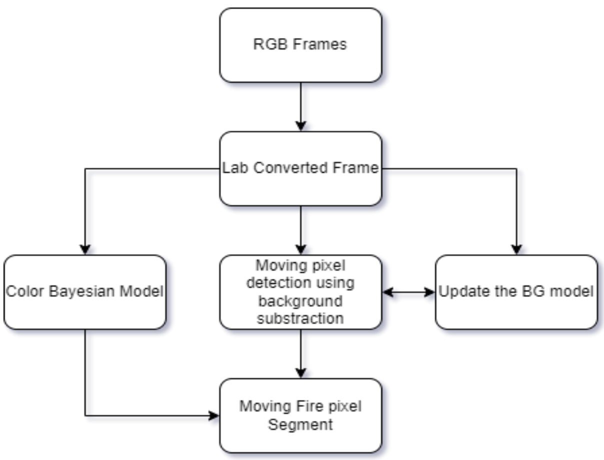

Figure 2: Workflow of the Flame Segmentation methodology

Segmentation is the process of detecting the region of fire content using the Bayesian and thresholding methodology. After the thresholding for the high intensity pixels, binary image of certain region in identified as flame pixels. This algorithm includes techniques like estimation of the background and segmenting the pixels. The segmentation of the background image and the foreground pixels is done by using Bayesian Interference algorithm. Repeated filters are applied to reduce the additional interferences. The pixels which are stable for longer duration are detected and separated. A pixel map in binary format is created using frame difference mapping technique. This model is highly effective based on the facts of less computational complexity and remarkably adaptive [5].

The flowchart illustration of the proposed segmentation system for the detailed explanation of the step-by-step process is given in the *figure 2*.

3.3 Feature Extraction
This step is designed to identify the corresponding target that maps the raw data into a canonical form computationally that describes the target. Two new optimal flow estimators Optimal Mass Transport (OMT) and Non-Smooth Data (NSD) are introduced in this proposed model to overcome the disadvantages and limitations faced in the conventional models. The motion attributes of the flame are applied on the obtained fields for the better estimation. Thus, these features efficiently distinguish between the flame and non-fire component based on their movement which is processed using the dataset extracted from the real footage of forest fire.

3.4 Classification
Special algorithms were used to estimate the input parameters and to form decision output regarding the presence of flame in the frame. Deep learning algorithms are employed for the classification of fire and non-fire frames in an image or video. A new architecture called FastFlameNet was proposed and explained in detail in this article. FastFlameNet model is designed by customizing the CNN model to the layer architecture in *figure 3.*

4. METHODS AND DISCUSSION
The proposed methodology is simulated using the MATLAB R2018a Simulation tool. The simulation is done in different modules and each module is briefed as follows.

4.1 Background Subtraction
Background subtraction is an important module which is done during the pre-processing process in the optical based frameworks. This module is used to extract the static and moving objects in the background of an image. In case of flame detection application all the static objects are identified and clustered and the moving objects are identified and marked. Then in an image or in a video frame the static background is subtracted to get the corresponding moving objects alone. In the proposed model the moving objects are flames hence accurate foreground implementation should be obtained. But when the shadows of the moving trees also fall in the image it is also considered as the foreground object which may deviate the detected results. Mis-prediction of the shadows for the smoke or flame pattern may end up in the false alarm [1].

Hence Pixel corresponding segregation is done to mark the colour contours and features of each pixel. In this module only few frames are considered for the pre-processing of the image or video footage. Probabilistic foreground segmentation algorithm is employed for this purpose along with Bayesian Inference model. The estimated frames are weighted heavily against the older extraction in order to accommodate the variable Illumination. Additional interferences like added noise are removed using the filtering operation.

Also, the pixels which are identified to be stable for long duration are considered as the static object and are subtracted from the foreground pattern. Additionally binary maps for the moving pixels are formed using the binary frame difference model. This module is considered for the implementation due to its beneficiary features like high adaptability and low computational complexity [5].

4.2 Optical Flow Detection
The sequence of image patterns is transformed into predicted fields with the help of the estimators. These estimators facilitated more detailed information extraction from the image patterns [6]. The correspondence between the pixels in the current and previous frames are obtained through the estimator computations. The optical flow constraint computation is facilitated with the following differential *equation (1).*

$$\frac{d}{dt} I = I_x u + I_y v + I_t = 0 \qquad \text{----- (1)}$$

Where *I (x, y, t)* correspond to the Intensity of the Image sequence with the spatial coordinates *(x, y).*

Optimal Mass Transport (OMT) Algorithm
The appearance of the fire cannot be identified using classical or traditional approach for two reasons (i) Flames doesn't provide adequate information to process through the equation (1) as the spatial and temporal intensity of the flames varies rapidly with the increased pressure and heat dynamics. (ii) Regularization of the smooth filter is counterproductive to estimate the motion of the flames, with expected amount of turbulence. Hence Optimal Mass transport algorithm is used for the estimated modelling of the flame identification.

4.3 Flame Direction Estimation Using FastFlameNet
Big data algorithms are used to handle the large amount of data processed in the application of the deep learning algorithms. Artificial algorithms are designed to train the machine to gain experience from the huge data set for easy recognition of the required target. CNN is a well-known type of AI algorithm that is often used in processing image and video in optimal estimation frameworks. Thus, deep learning algorithms are trained by CNN algorithms to identify and detect the flame patterns in the image and video [7].

CNN is selected for this image distinguishing activity because it is identified as the most efficient algorithm among Deep learning algorithms. The primary advantage of using CNN is that it automatically distinguishes between the relevant and

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irrelevant attributes in an image without any human intervention. The other advantages of using CNN are equivalent representation, sparse interactions, and attribute sharing. The entire shared weights and the local connections are used in full-fledged form to utilise the two-dimensional data. The proposed architecture of the FastFlameNet is illustrated in *figure 3* as follows.

Stochastic gradient descent (often abbreviated SGD) is an iterative activation function used for optimizing an objective function with suitable smoothness properties (e.g., differentiable or subdifferentiable). SGD is much faster but the convergence path of SGD is noisier than that of original gradient descent. This is because in each step it is not calculating the actual gradient but an approximation. So, we see a lot of fluctuations in the cost. But still, it is a much better choice. The adequate input of each layer is distinguished with the dimensional attributes like height, width and depth. Generally, the height and width are considered to be the same value. The depth is considered as the channel number of the corresponding channel. There are many filters available in the input side which are also organized in a three-dimensional pattern as the same as the input. Each filter is represented by k. These kernels are considered as the basis for the local connection which shares the similar parameters required to generate the feature maps denoted as h_k.

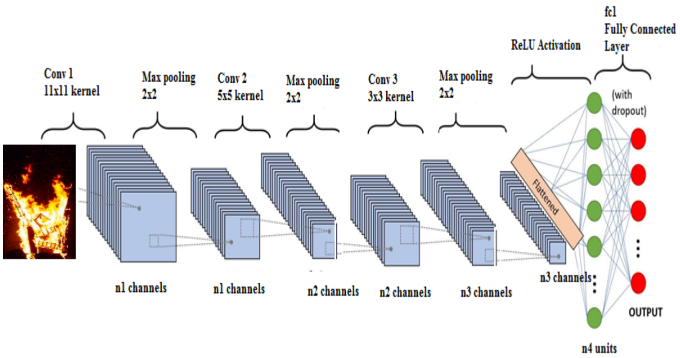

Figure 3: Block diagram of FastFlameNet Architecture

The size of each map is convolved with each layer and the dot product of input and weights are calculated as follows

$$h_k = f(W_k * x + b_k) \qquad \text{--- (2)}$$

The process is continued by down sampling the feature map in the sun-sampling layers. This reduces the parameters and the training process is speeded up as a result to effectively handle the over fitting issue. The pooling function is applied to the feature map in the adjacent area where the kernel size is limited to 2. Three different convolution layer frameworks of size 11x11,5x5 and 3x3 are used in this implementation.

Finally, the Fully Connected (FC) layers receive the mid and low-level attributes and create a high-level abstraction. The corresponding classification points are generated through the last layers of the Softmax.

These scores represent the probability of the flame direction. The detailed attribute information of the FastFlameNet is given in *table 1*.

Table 1: Parameter specification of the proposed classification methodology

Layer Name	Size	Kernel Size	Feature Maps	Stride
Input Layer	64 x 64 x 1	-	-	-
Convolution layer 1	-	11 x 11	32	1
Max pooling 1	-	2x2	-	2
Convolution layer 2	-	5 x 5	16	1
Max pooling 2	-	2x2	-	2
Convolution layer 3	-	3 x 3	8	1
Max pooling 3	-	2x2	-	2
Fully Connected Layer	2	-	-	-

5. RESULTS AND DISCUSSION

In this section, evaluation of proposed FastFlameNet architecture in detection and classification of fire flames in real time video is performed. We also compared our key performance indices with existing method of Dilated CNN [19]. To prove our proposed algorithm efficiency in the detection of flames and their direction, three different density of fire flame videos are considered as low, medium and high density of flames. We take the videos with the memory range of 20MB-45MB. MATLAB 2020a is the simulation platform which we used to create and evaluate our proposed FastFlameNet. The configuration parameters defined in simulations are listed out in the *table 2* and FastFlameNet Training parameters are mentioned in *table 3*.

Table.2. Simulation Configurations

Parameter	Value
Frame Rate	30 frames/sec
Frame Duration	25 sec
Frame Width	256
Frame Height	256
Data Rate	13.9Mbps
Total Bit Rate	14Mbps
Initial BG frames	5

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Table 3: FastFlameNet Training Configurations

Parameter	Value
Activation Function	Stochastic Gradient Descent Method (SGDM)
Number of Epochs	20
Number of Iterations	100
Initial Learning Rate	0.1
Minimum Batch Size	64

For any video processing, we begin the process with the frame conversion. For the number of frames in the testing video, frame conversion and image conversion are performed by sequence. *Figure 4* shows the converted frames as image array.

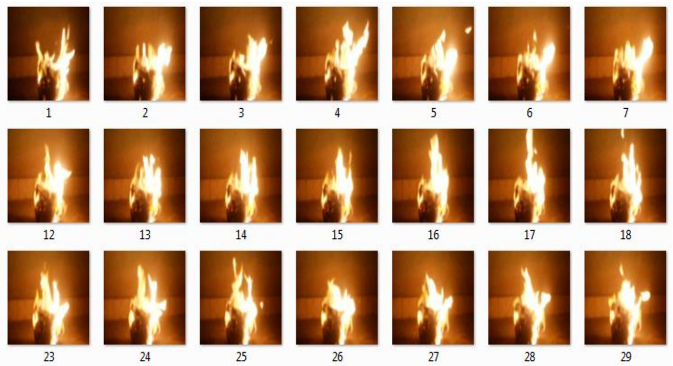

Figure 4: Video to Frame Conversion

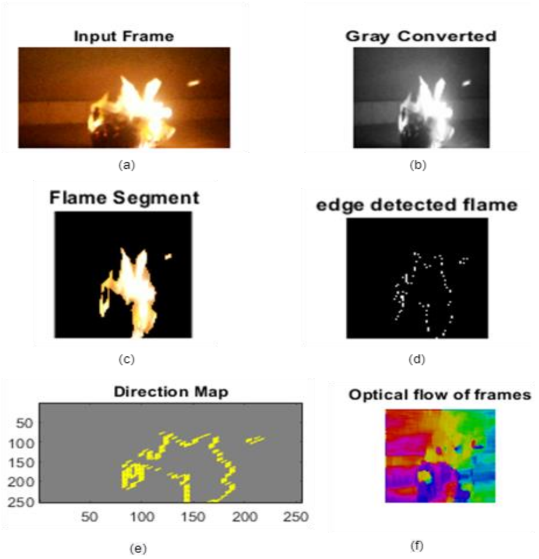

Figure 5: Flame segmentation of the image a) Input frame, b) gray converted frame, c) flame color segment, d) edge of segment, e) optical flow-based direction map, f) flow of flame content

Figure 5 depicts the evaluation results of segmentation performance in the proposed methodology. For every frame, RGB to gray conversion is performed to implement the thresholding. After the bayesian color model segmentation, the segmented color region is fed into the optical flow-based feature extraction. Features are considered as two type, directional feature and flow of flame feature. These are illustrated in *Figure 5-(e) and (f).*

Figure 6 illustrates the process of CNN training for the layer architecture of proposed FastFlameNet. For the number of epochs, the process will be continued upto 20. But in the epoch of 13 itself, it reached the maximum accuracy of 100%. So, in too fast manner our proposed Network is working for the classification of flame direction and result is shown in *figure 7*.

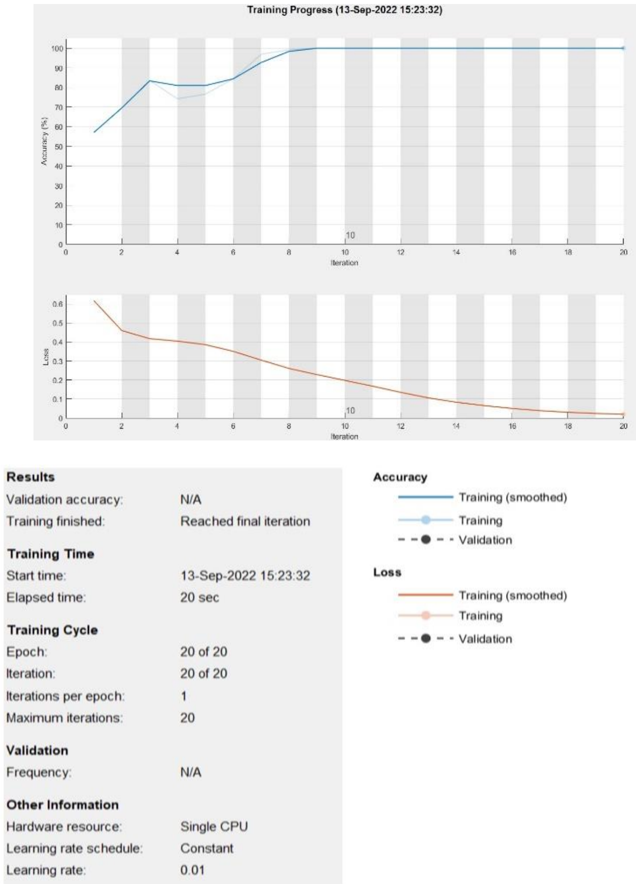

Figure 6: FastFlameNet Training Progress

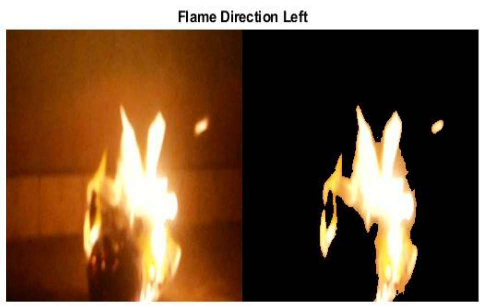

Figure 7: Flame direction classification from FastFlameNet

Error Matrix or confusion matrix is a special type of array that is used in the neural learning algorithms to characterize the efficiency of the proposed classification model on a known set of test data using supervised learning model. The advantage of a confusion matrix is the use of performance metrics calculation. TP, FP, TN, FN are predicted from confusion matrix only. From these four values remaining all metrics are evaluated. This matrix has a summarized detail of the correct and false prediction done in each class.

The row of the confusion or error matrix refers the class of prediction and the columns refers to the actual class. The corresponding true and false prediction is entered in the *figure 8.*

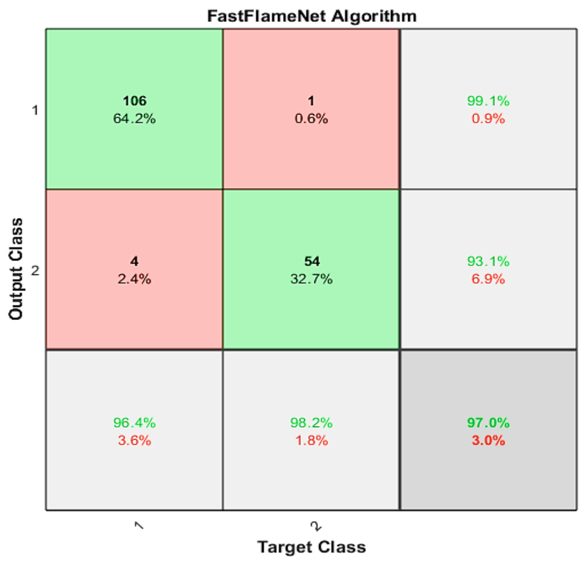

Figure 8: Confusion matrix of the FastFlameNet model

Table 4: Attribute comparison of the existing and proposed framework

Attributes	Existing model (Dilated CNN)	FastFlameNet model
Accuracy	90.3030	96.9697
Error rate	9.6970	3.0303
Precision	93.5185	99.0654
Recall	91.8182	96.3636
Specificity	87.2727	98.1818
F1 score	92.6606	97.6959
Correlation	78.4070	93.3496
False positive rate	12.7273	1.8182
Kappa Factor	78.3784	93.2735

To analyse the performance efficiency of the proposed FastFlameNet model, the attribute comparison of the proposed model is done against the existing model of flame detection methodologies. The obtained attributes are listed in the *Table 4*. From the table it is clear that the False detection rate of the FFN methodology is very less which confirms the increased correlation between the pixels in the proposed model which increases the precision and accuracy of the proposed model when compared with that of the existing Dilated CNN model.

Thus, the performance efficiency of the FFN model is proved to be greater than the existing model (Dilated CNN) with the augmented attribute values which is clearly depicted in the Graphical representation as shown in *figure 9*.

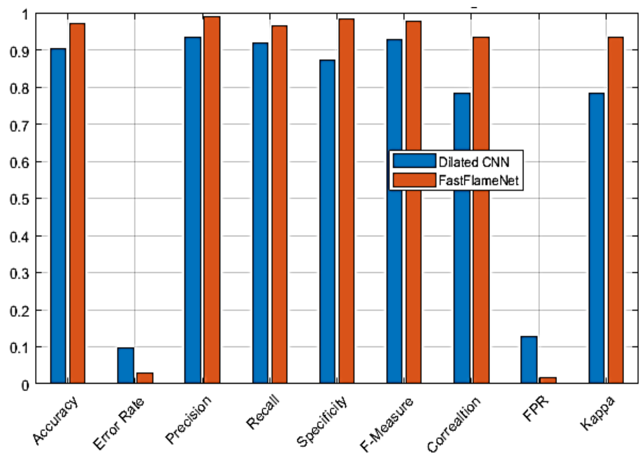

Figure 9: Key Performance Index of the proposed model and dilated CNN model

6. CONCLUSION

The proposed and implemented model is a novel deep learning architecture network of FastFlameNet for categorizing fire flame direction from the real time video frames captured for surveillance in domestic and forest sections. The proposed model is copiously programmed and entails no manual involvement. The proposed model is effective with less false predictions with increased accuracy of the detection. This method has many advantages like the use of repeated convolution filter, minimized kernal size, minimal layers and the customized dataset. This model was implemented using MATLAB simulator through iterative testing of the operators and the optical flow algorithms. The minimal layers used in the proposed model is identified to augment the performance efficiency of the FastFlameNet framework. Minimal layers directly influence the time complexity of the model with less computational time.

The comparative study made between the dialed CNN and FFN model proves the superiority of the proposed model with augmented parameter values. However, this model is not suitable for large datasets. The future work involves the design of light weight model and sturdy detection methodology for large datasets.

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