An Efficient Multi-Feature Best Decision Based Forest Fire Detection (MF-BD-FFD) From Still Images

M. Senthil Vadivu, M.N. Vijayalakshmi

Abstract: Fire attack in forest makes major degradation in the forest environment and ecosystems. Forest fire detection in the early stage can prevent major causes due to fire attack. A novel digital image processing based on multi-feature best decision-based forest fire detection (MF-BD-FFD)is proposed in this work. To increase the sensitivity of detection, color and texture feature with hybrid decision making algorithms such as artificial neural networks (ANN), Support Vector machine (SVM), k- nearest classifier (KNN) is used and optimized output will be selected. By using proposed method, the accuracy of the system is increased with a factor of 5% when compared to the conventional technique.

Keywords: Forest Fire Detection (FFD), Artificial Neural Networks (ANN), Support Vector Machine (SVM), k- nearest Classifier (KNN), Digital Image Processing (DIP)

I. INTRODUCTION

Fire is a key player in the forest degradation. There are human-caused and natural caused forest fires. It is exceptionally basic to recognize the forest fire at its underlying state; in light of the fact that greater the fire, harder is to douse it. Monitoring techniques using remote sensing for detecting deforestation caused by clearing or forest fires are well established. There are a few techniques for observing the forest fire. However, the increased popularity of digital cameras and the huge development in imaging science has made forest fire detection using image processing algorithms more cost-effective and simpler compared to other traditional methods like sensors, satellites etc. There is a particular need for detecting and monitoring unplanned activities, such as illegal logging and low impact fires since these are often the initial step to deforestation. Some studies have focused on monitoring forest degradation, either through the use of Landsat, or very high-resolution satellite images such as IKONOS. Earth observation data used for monitoring such activities must, therefore, meet specific requirements in terms of spatial and temporal resolution. The REDD Fast Logging Assessment and Monitoring Environment Project (REDD-FLAME), financed under the Seventh Framework Program (FP7) of the European Commission, goes for the meaning of such forest checking strategies [1].

The fire has certainly one of a kind attributes that segregate it from other real-life ordinary items. One important attribute is its colour. It is anything but difficult to distinguish a fire by utilizing its colour data. Particularly in the case of forest fire, it is easy to recognize the fire colour from the green colour of the forest. Fire detection at night is much easier than the same during the daytime because of the high luminance characteristic of fire flames [2]. However, there are several other objects that have similar colour characteristic to that of a fire flame. For example, bright sunlight can be mistaken for a fire at daytime. Reddish yellow coloured flowers, people wearing fire coloured dresses, bright lights etc., can also be mistaken for fire. The aforementioned problem of fire coloured ordinary objects can severely affect the performance of the fire detection system. Hence most of the fire detection systems based on image processing algorithms deploy two steps in the operation. The first step finds the candidate pixels for fire detection and the second step tries to improve the detection accuracy by eliminating the errors. The primary technique for detecting the presence of fire in an image is to classify pixels that have certain fire characteristics in common [3] This characteristic includes texture, shape, colour. The simple and most common method used for this purpose uses the colour characteristic of fire flames [4]. A training set is created by analyzing the colour clues of manually segmented fire regions. This training data is used to classify fire like pixels. The remaining operations are performed on these obtained candidate pixels. Other important characteristics of fire flames like its flickering motion, arbitrary shape etc., can be used to distinguish between fire and fire-like pixels. In the case of videos, the motion analysis can be done on consecutive frames to reduce errors. Presence of smoke can also be used to reduce the rate of false positives. The existing method cannot detect fire region properly; however, many other features have to be taken into consideration [5]. A novel cobination of hybrid classifier and feature extraction method that is capable of classifying an object as fire or no fire in still fire images is proposed in this study. The colour of fire area can range from red yellow to almost white. In this proposal, a Multi-Feature metaclassifier with optimized output-based forest fire detection is explained to estimate the forest fire in an efficient manner when compared to the conventional forest fire detection algorithms.

II. EXISTING WORK

Keeping in mind the end goal to recognize the misleading information about forest fire from the traditional fire recognition system [6], a PC vision-based fire location calculation is used for accurate information. The proposed fire location calculation comprises of two principle parts: fire color modeling and motion detection.

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Another fire shading model is created in CIE L*a*b* color space to distinguish fire pixels. The proposed fire color model is tested with ten diverse video sequences including different types of fire. The experimental outcomes are very promising as far as effectively characterizing fire pixels as indicated by color data as it were.

In this strategy detailed perception of the color distribution in RGB space [7] is utilized to remove the candidate fire pixels is proposed. After removing the falsely extracted fire-like pixels, reestablish the erroneously expelled fire faults and holes and recreate the fire region. The experimental results are compared with other methods. It shows a higher accuracy and robustness of fire detection by our proposed method. A high accuracy is necessary and important for the next step to detect fire dynamic features.

In this technique fire-recognition is to receive a RGB (red, green, blue) model based chromatic and confusion estimation for removing fire-pixels and smoke-pixels [8]. The decision function of flame pixels is chiefly reasoned by the intensity and saturation of R segment. The separated fire-pixels will be confirmed on the off chance that it is a genuine fire by the two elements of development and clutter, and further smoke. In light of iterative keeping an eye on the developing proportion of blazes, a fire-alert is given when the caution raising condition is met. Trial results demonstrate that the created system can accomplish completely programmed observation of flame mischance with a lower false alert rate and in this manner is extremely attract for the critical military, government disability, business applications and so on, at a general cost.

This method combines the unique color and texture features of the fire flames [9]. The RGB images obtained from digital cameras are used as inputs. The mean value estimation is used to assume the presence of fire flames in an image. Its presence is confirmed by performing the background elimination. Color rules defined for the RGB, HSV, and YCbCr color spaces are used to segment the fire regions. The HSV and YCbCr color spaces are used because of their capability to separate intensity (luminance) and color characteristics (chrominance). One of the unique characteristics of the fire flame pixels is its high intensity value. These color spaces help to take this characteristic into account thereby reducing a lot of errors. Finally, the result is made more accurate by using the texture analysis. The Gray-Level Co-occurrence Matrix (GLCM) is used to calculate five texture features of the fire flames. The proposed method is tested on a set of fire and non-fire images and it achieves a high detection rate and low false rate.

The strategy depends on a block based feature extraction technique [10], which involves investigations about local information in partitioned regions thereby decrease effect on computational information. Local features of fire block are separated from detailed characteristics of fire objects, which incorporate fire color, fire source fixed status, and disorder. Each local feature has high detection rate and filter out different false-positive cases. Global analysis with fire texture and non-moving properties are applied to further reduce false alarm rate. The system is composed of algorithms with low computation. In this technique A binary contour image of fire [11] is accustomed to grouping fire or no fire in picture for flame detection. The shade of flame area can go from red yellow to relatively white. Along these lines, here it is challenging the distinguished reparatory is really fire or no fire. This system contains five areas. Firstly, the digital image is taken from dataset and the digital image is sampled and mapped as a grid of dots or picture elements. In this technique picture isolate RGB Color range Matrix. At that point a few guidelines to choose yellow color range of the picture later on changed over the picture to twofold territory. At last, double shape picture of fire data that recognize the fire.

III. PROPOSED TECHNIQUE

Multi-Feature Best Decision Based Forest Fire Detection (MF-BD-FFD) is proposed in this work. Block diagram for MF-BD-FFD technique can be outlined in Figure 2. Proposed method extracts various features such as texture and color then performing classifications. For efficient classification, hybrid classification is used. In this project, multi classifiers such as Support Vector Machine, K-nearest classifier, Artificial neural networks are used as a classifier. Best decision is chosen by using maximum vote count. The detailed explanation of various modules used to perform the proposed method is explained below:

Data Acquisition

Image Acquisition is the primary step in forest fire detection. Normally, satellite image for the particular fire region is captured and processed. For research work, highly standard databases are available with labelling to perform training and validation process. 24-bit colour images are preferably used to perform operation with less computational complexity. Some sample images with fire region can be shown in Figure 2.

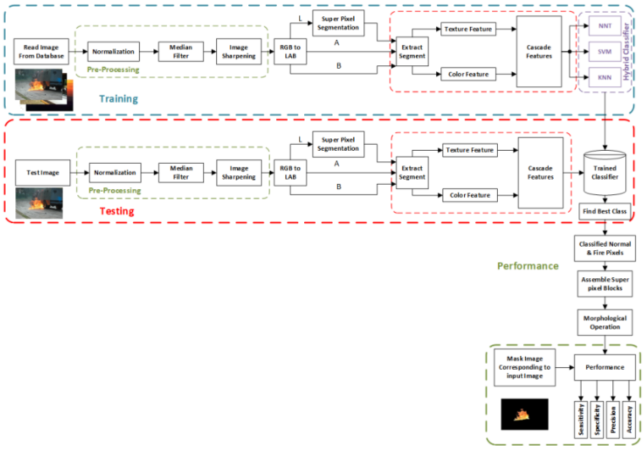

Figure 1: Block Diagram of Proposed method

Pre-Processing

In a pre-processing step, three major sub-operations are performed that are 1. Normalization, 2. RGB to LAB Conversion 3. Median filtering 4. Image sharpening. Normalization is performed to reduce the computational error while processing the images mathematically and logically. In normalization, 8-bit images are converted into 64-bit double precision IEEE datatype.

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It can reduce the round-off error while processing. RGB to LAB conversion is used to get better colour property of fire region [12]. RGB to lab conversion can be performed after doing an intermediate operation that is called XYZ conversion. The mathematical formula which is used to convert RGB to XYZ can be shown in (1).

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.412452 & 0.357580 & 0.180243 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{1}$$

$$L^* = 116 f\left(\frac{Y}{Y_n}\right) \tag{2}$$

$$a^* = 500\left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right) \tag{3}$$

$$b^* = 200\left(f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right) \tag{4}$$

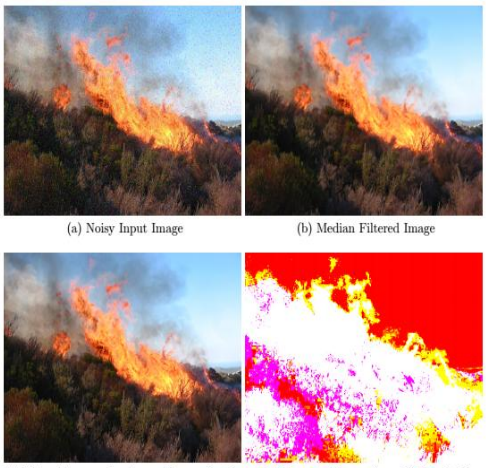
similarly Lab to RGB operations also performed after doing intermediate operation of XYZ conversion. Equations used to perform reverse operations can be given from eq(6) to eq(8)

$$X = X_n f^{-1}\left(\frac{L^* + 16}{116} + \frac{a^*}{500}\right) \tag{5}$$

(a) Sample Fire Image-1 (b) Sample Fire Image-1

Figure 2: Sample Fire images used for Processing

Small cracks and noise in the images which are occurred while capturing can be easily removed by performing medial filtering. Normally, after performing median filtering operation, the image will be blurred due to median operation which is used for denoising operation. This effect can be retained by performing an image sharpening operation serially. Likewise, the edges of the pictures can be enhanced by utilizing image sharpening operator. which is used for denoising operation. This effect can be retained by performing an image sharpening operation serially. Likewise, the edges of the pictures can be enhanced by utilizing image sharpening operator.



(a) Noisy Input Image (b) Median Filtered Image

(c) Filtered Image using Image Sharpening Operator (d) Converted Image from RGB to LAB

Figure 3: Various Pre-processing operation for Input Image

$$Y = Y_n f^{-1}\left(\frac{L^* + 16}{116}\right) \tag{6}$$

$$Z = Z_n f^{-1}\left(\frac{L^* + 16}{116} - \frac{b^*}{200}\right) \tag{7}$$

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 3.240479 & -1.537150 & -0.498535 \\ -0.969256 & 1.875992 & 0.041556 \\ 0.055648 & -0.204043 & 1.057311 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} \tag{8}$$

Super Pixel Segmentation

The concept of superpixel was first introduced by Xiaofeng Ren and Jitendra Malik in 2003 [13]. Super pixel is a gathering of associated pixels with comparative colours or grey levels. Super pixel segmentation is separating a picture into many non-overlapping super pixels. Instead of working with just pixels, Image regions can be utilized to feature extraction. Superpixel segmentation is implemented in the intensity (L) component of LAB color space. The structural information of image can be achieved only in the L components of Lab Color space. For color feature extraction and texture extraction all the color components have been used There are two major advantages of using super pixels.

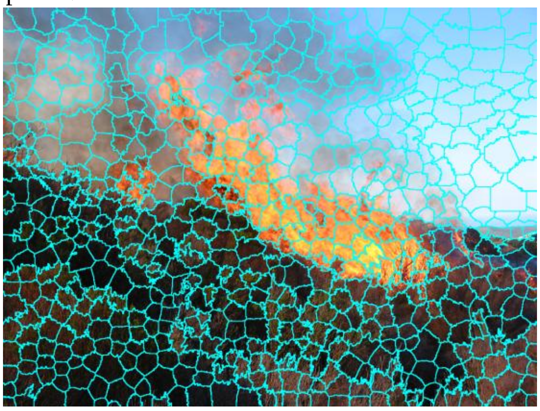


Figure 4: Super pixel Segmentation of Preprocessed Image

Superpixel segmentation has been applied to many computer vision tasks, such as semantic segmentation, visual tracking, image classification, and so on.

Feature extraction one of most import step for distinguishing fire and fire like pixels from images. The fire has certain characteristics that can be distinguished from other kind of pixel. Such highlights are colour, texture and shape. Colour features can be directly grouped from LAB colour space. Texture features are obtained from histogram bins of the image and Shape features are extracted from template matching. These features are one of the prominent sources to detect and classify the fire region in the image. Finally, these features are used for training and testing in various classifiers such as SVM, ANN and KNN.

Centre Symmetric Local Binary Pattern (CSLBP)

Center Symmetric-Local Binary Pattern (CSLBP) is textured based operator which is mostly used as key point descriptor, it is 256-length descriptor to represent single keypoint or a_ne patch. This operator is an extension of Local Binary Pattern (LBP) operator.

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The CSLBP descriptor is computationally simple, e_ective, and robust for various image transformations such as illumination change and image blurring. Utilizing CSLBP is extremely productive for brightening and blur kind of picture change. It restores the unnormalized CSLBP histogram of length 16. One can easliy normlize according to his application. Generally, it is utilized as keypoint descriptor. Identify the key points, measure the neighborhood _x around the keypoint and after that figure the CSLBP descriptor. In any case, for similicity, beneath case register the picture level descriptor rather neighborhood keypoint descriptor.

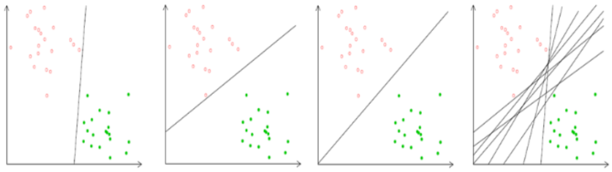

Figure 6: Graphical Representation of CSLBP

System Training

In machine learning, SVM are directed learning models that should have related learning calculations should utilize the information and perceive designs for characterization and relapse investigation SVM can perform either linear or non-linear classification [14]. Figure 3. Shows how decision making is performed in SVM. In supervised training, the preparation information comprises of an arrangement of preparing cases, where every illustration is a couple comprising of an information and an expected yield esteem. A regulated learning algorithm investigates the preparation information and after that predicts the right classification for given informational index input. Example, the teacher teaches the student to identify orange and lemon by giving some features of that. Next time when the student can see lemon or orange can easily classify the object based on his gaining from his educator, this is called directed learning. He can recognize the object just on the o_ chance that it is lemon or orange, yet in the event that the given question was grapes, the understudy can't distinguish it. The Margin of a direct classifier has the width by which the length of limit can be expanded before hitting the information purposes of an alternate classification. The line is projected to pick having the most astounding edge between the two datasets. The information focuses which lie on the edge are called Support Vectors. The subsequent stage is to discover the hyperplane which best isolates the two classes. SVM plays out this by taking an arrangement of focuses and part them utilizing diverse application-particular scientific crecipes. From that, we can locate the positive and negative hyperplane.

Artificial pattern recognition-based classifier is utilized to perform the prediction process. While training SVM, neural network and KNN are parallelly trained and keep ready for the testing operation. For training of ANN, training data prepared by performing feature extraction and giving proper lab belling vector. The specification used for ANN can be presented in table 1.

To perform training number of hidden layers used is 100. From various experimental run, we found that 100 is the best value for the number of hidden layers. Number of hidden layers is precisely proportional to the complexity of the algorithm. Training performance of the ANN can be displayed in figure7. From the graph, it is clear that the cross-entropy is gradually reducing while number of iteration increases. It indicates that the performance of the taring is good. Similar receiver operating curve (ROC) can be shown in figure 8. KNN also trained by using the same training vector and labelling matrix using fitcknn function of MATLAB.

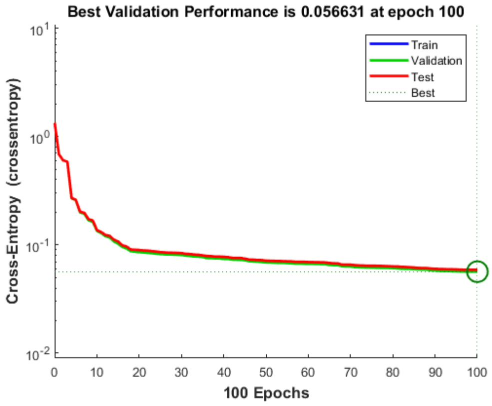

Figure 7: Training Performance of NNT

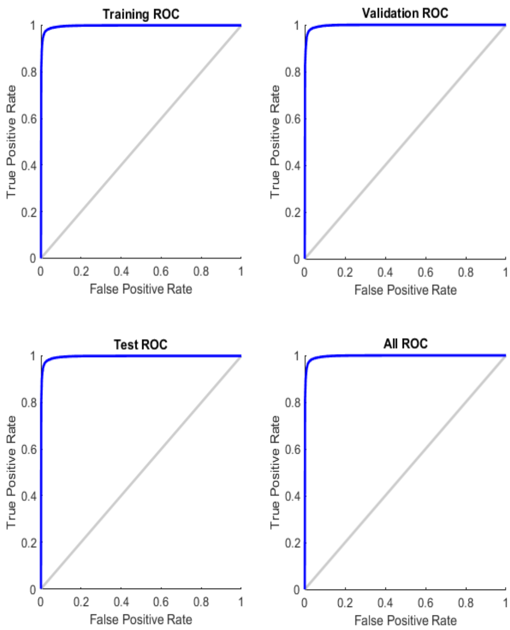

Figure 8: ROC curve for NNT training

Table 1: ANN Specification Table

Sl.No	Parameter	Parameter Value
1	ANN Type	Pattern Classifier
2	Number of Hidden Layer	100
3	Number of Inputs	52
4	Number of Outputs	1
5	Training Function	Scaled conjugate gradient backpropagation

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System Testing

Testing is done by reading individual forest _re images. For testing, same operation such as preprocessing, feature extraction is performed and feeding features parallelly into the classifiers such as ANN, SVM and KNN.

Maximum voting-based decision will be deemed to perform the best decision-making process. Mathematical representation of voting process can be shown in eq(9), eq(10), eq(11) and eq(12).

$$Vote_{All} = [SVMDecision, ANNDecision, KNNDecision] \qquad (9)$$

$$vote_1 = find(Vote_{All} == 1) \qquad (10)$$

$$vote_0 = find(Vote_{All} == 0) \qquad (11)$$

$$BestDecision = Max(vote_1, vote_0) \qquad (12)$$

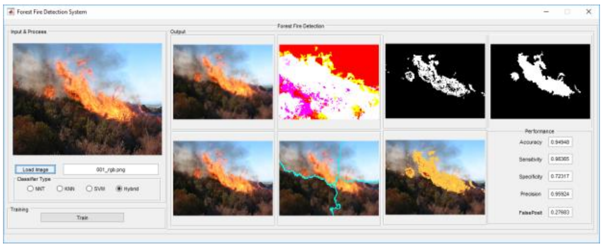

Figure 9: Graphical User interface Used

IV. RESULT AND DISCUSSION

Various kinds of images used to validate the performance of the proposed algorithm. Sample images used from cosican fire image database can be shown in figure 2. Detailed explanation of database and image properties is explained in below section. To validate the proposed system, sensitivity analysis is performed. Graphical User Interface developed for testing can be shown in Figure:9. Various intermediate results and performance values also displayed in gui. Training for new category also can be done by adding the corresponding image and mask in to the proper folders.

Dataset

Corsican Fire database [15] is used to validate the implemented algoritms in matlab. The database consists of images of forest _res have been reported in Corsica. This database consists of the RGB image and their corresponding ground truth image which are black and white image with fire segmented region. The original _re image is labeled and saved with filename rgb.png

and corresponding ground truth image is labeled with the same file name but filename gd.png. All the fire image and their corresponding template images are in .png format.

Image-1 (b) Mask of Image-1

(c) Image-2 (d) Mask of Image-2

Figure 10: Sample images from Corsican Fire database

Experimental Setup

Proposed algorithm is simulated in MATLAB2017a version in an i5 system with 4GB RAM. Corsican Fire database images are used for testing the algorithm. To avoid the computational complexity the images are down sampled by a factor of 2. Resolution of the image is directly proportional to the computation time of the algorithm. From Corsican Fire database 60% of images are used in training stage and 40% of images are used for testing the proposed system. Figure 11 shows the samples of non-fire images used to test proposed algorithm.

Result Analysis

MF-BD-FFD algorithm is subject to various combination of fire images. Some of the sample images used for the proposed work can be shown in ref fig: sample Images From Darabase. A ratio of 60:40 is used for training and testing operation. Table 2 shows the performance of different images with different performance metrics. From the table, it is very clear that the accuracy and other performance values are maximum with respect to different images.

(c) Image-2 (d) Predicted Image

Figure 11: Non-fire Images Used for Testing

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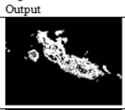
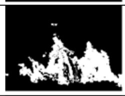
Accuracy Assessment

To perform sensitivity analysis, test image will be compared with reference images of the subject for each class. For analyzing the algorithm performance, multiple numbers of images with different classes to be used. For performance measurements, four standard performance measurements will be utilized. For the performance analysis such as True-positive (tp) pixels, True-negative pixels(tn), False-positive pixels (fp), and False-negative pixels (fn). True-positive pixels (tp) are performed in the resultant image with the reference of ground truth image. By using the above-mentioned values, sensitivity and specific and other evaluation metrics can be determined. The relevant pixels of the detected fire can be found by using sensitivity. Irrelevant pixels can be determined by using precision, the formula for precision and sensitivity and other measures are is given below:

Table 2: Performance Measure for Various Images

Input Image	Mask Image	Segmented Output	Metamorphosis	Fig
			Accuracy Sensitivity Speci_city Precision FPR	0.94948 0.98365 0.72317 0.95924 0.27683
			Accuracy Sensitivity Speci_city Precision FPR	0.83496 0.98798 0.4828 0.81469 0.5172
			Accuracy Sensitivity Speci_city Precision FPR	0.85866 0.99615 0.19509 0.85659 0.80491
			Accuracy Sensitivity Speci_city Precision FPR	0.83413 0.99661 0.15788 0.83124 0.84212

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \quad (13)$$

$$Sensitivity = \frac{tp}{tp + fn} \quad (14)$$

$$Specificity = \frac{tp}{tp + fn} \quad (15)$$

$$Precision = \frac{tp}{tp + fn} \quad (16)$$

$$FalsePositiveRate(FPR) = \frac{tp}{tp + fn} \quad (17)$$

V. CONCLUSION

A novel fire detection based on multi-feature best decision-based forest fire detection (MF-BD-FFD) is proposed. To increase the sensitivity of detection, color, shape and texture feature with hybrid decision making algorithms such as artificial neural networks (ANN), Support Vector machine (SVM), k- nearest classifier (KNN) is used and optimized output will be selected. The proposed method was tested on both fire and non-fire images and it produced best results. The CSLBP descriptor is used for feature extraction it has the advantages of computationally simple, effective, and robust for various image transformations such as illumination change and image blurring. So overall our proposed outperforms other fire detection method. By using proposed method, the accuracy of the system is increased with a factor of 5% when compared to the conventional technique.

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