A Technique for Burning Area Identification Using IHS Transformation and Image Segmentation

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Abstract: *In this paper, we have designed and developed a technique for burning area identification using Intensity Hue Saturation (IHS) transformation and image segmentation. The process of identifying the burnt area in proposed technique consists of four steps such as: IHS transformation, object segmentation, identification of smoke area using Feed-Forward Neural Network (FFNN) and discovering burning areas from the smoke segments. Here, satellite image collected from NASA is utilized for the experimental study of the proposed research. The images obtained from the NASA is given to HIS transformation that convert the RGB image into intensity, hue, saturation transformed image so that, this process is suitable for segmentation process. After the transformation of image, object segmentation technique is done based on K-means clustering algorithm. Subsequently, FFNN is used for identification of smoke area from the segments. After identifying the smoke segment, the burning area is identified through directional analysis. The proposed burnt area identification technique is analyzed with the help of sensitivity, specificity and the accuracy. Finally, experimental results say that, the proposed technique is achieved the overall accuracy 2.6%, which is better than the existing approach.*

Keywords: *Burning, segmentation, K-means, FFNN.*

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1. Introduction

Remote sensing is a versatile tool for exploring the earth and it involves the application of instruments or sensors to "capture" the spectral and spatial relations of objects and materials discernible at a distance. Aerial and satellite images [2, 9, 10, 12, 21] known as remotely sensed images, permit accurate mapping of land cover and make landscape features understandable on regional, continental and even global scales. It has been extensively made use of for the monitoring of the earth surface to decide on the changes in land use and land cover [18]. It can also, be used in creation of mapping products for military and civil applications, evaluation of environmental damage, monitoring of land use, radiation monitoring, urban planning, growth regulation, soil assessment, crop yield appraisal and forest monitoring [15].

Forest resources are one of the most important on earth and the basis of biological diversity. They not only provide a variety of valuable wood and raw materials for production, but also, various foods for humans. Furthermore, forests can affect the climate by reducing soil erosion and preventing and mitigating drought, wind and other natural disasters. However, in recent years, many forest fires have broken out in various regions of the world, causing tremendous losses. Forest fires have been drawing increasing attention in recent years because of their tremendous effect on humans, the environment, wildlife, ecosystem function, weather and climate. An accurate monitoring and mapping of the spatial and temporal distribution of forest fires is important because it contributes to fire effect assessment and control, as well as to a number of ongoing studies on land use, land cover change, climate change and so on [22].

In forest fire related studies, fire burned landscapes are suitable targets for remote sensing research because of the obvious physical changes the fire has on the land cover. Characteristic changes of burned areas include canopy consumption, ground charring and soil color alteration. These characteristics are detectable using satellite sensors if the patch size of the burn is within the resolution range of the satellite sensor. Remote sensing is a useful tool for mapping the extent of the burn, understanding the biological responses due to differential surface heating (i.e., fire severity) and quantifying the extent and pattern of these burned areas [24]. Several methods have been proposed for mapping burned areas from either multi-temporal or single post fire images: Supervised classifications such as maximum likelihood, decision trees and neural networks, linear transformations such as tasselled cap and principal component analysis, spectral unmixing techniques and logistic regression models [17].

According to the literature, the spectral signature of recently burned areas can be confused with the signature of shaded areas. Frequently, this occurs as a result of slope illumination and shadowing effects caused by the complex topography encountered in many forested areas. Moreover, it can result in a less accurate estimation of the burned area when multispectral classification, one of the most traditional methods used to extract information from remotely sensed data is applied to satellite sensor images. An alternative technique, object-based image identification, which deals with objects (group of pixels) that have been extracted in a previous image segmentation step, may be more accurate for burned area mapping [13]. In spite of, all the advantages, classification of remotely sensed imagery is a challenging subject because of the complexity of landscapes and the spatial and spectral resolution of the images being employed. Multispectral remotely sensed images comprise information collected over a large range of variation on frequencies and these frequencies vary over diverse regions [5, 19]. A considerable number of research efforts have been made to take advantage of neighboring pixel information and classification [7, 11, 19, 20] and applied for the classification of remotely sensed data.

In this paper, we have developed a technique for burning area identification using Intensity Hue Saturation (IHS) transformation and image segmentation. The process of identifying the burnt area in proposed technique consists of following steps such as: IHS transformation, object segmentation, Identification of smoke area using Feed-Forward Neural Network (FFNN) and discovering burning areas from the smoke segments. Here, satellite image collected from NASA is utilized for the experimental study of the proposed research. The images obtained from the NASA is given to HIS transformation that convert the RGB image into intensity, hue, saturation transformed image. After the transformation of image, object segmentation technique is done based on K-means clustering algorithm. Subsequently, FFNN is used for identification of smoke area from the segments. After identifying the smoke segment, the burning area is identified through directional analysis.

1.1. Structure of the Paper

The rest of the paper is organized as follows: A brief review of some of the literature works in burnt area identification is presented in section 2. The proposed burnt area identification technique is detailed in section 3. The experimental results and performance evaluation discussion is provided in section 4. Finally, the conclusions are summed up in section 5.

2. Related Researchers: A Brief Review

Literature presents several techniques for burnt area identification. Here, we review some of the work presented. Wang *et al.* [22] have focused on investigating the ability of selected satellite-derived indices, the Normalized Multi-band Drought Index (NMDI), Normalized Difference Water Index (NDWI) and the Normalized Burn Ratio (NBR), for detecting forest fires burning in southern Georgia, USA and southern Greece in 2007. Index performance was evaluated using Moderate Resolution Imaging Spectroradiometer (MODIS) fire products. Both, performance evaluations by image comparison and statistical analyses, indicated that active fire detection using NMDI was quite accurate. The successful application of NMDI for detecting fires in different areas proved that NMDI was not site-specific and was expected to be applicable to different areas for active fire detection. Holden and Evans [8] have compared three methods of classifying pre- and post-fire landsat data: dNBR classification using Composite Burn Index (CBI) field data to assign severity classes; fuzzy C-means classification of a dNBR image; local Getis-Ord statistic (Gi*) output applied to a dNBR image, classified using fuzzy C-means clustering. They used a Kappa statistic to evaluate the agreement of severity classes assigned to a pixel with its corresponding CBI plot. For two of the three fires, the C-means clustering of the dNBR and the Gi* output performed as well or better than dNBR images classified using CBI data, with strong agreement for moderate- and high-severity classes.

Sifakis *et al.* [16] have used MSG-SEVIRI geostationary data for fire detection and tracking over Greece acquired during the disastrous wildfire period in the summer of 2007. SEVIRI data were processed using an existing image processing algorithm for fire detection, which was fine-tuned according to Greek conditions and priorities (i.e., increasing its sensitivity at the expense of false alarms). The obtained results were assessed against reference information on fire events provided by the hellenic fire brigade. SEVIRI proved capable of reliably monitoring the consecutive and multiple fire events in the region of Peloponnisos. Based on these images, it was possible to quickly locate all burning areas providing a synoptic picture of the disaster that may support the authorities in the engagement of the appropriate human and technical resources. Anggraeni and Lin [1] have developed to measure fire induced deforestation in South Sumatra, produce a burned area map from a landsat TM image and compared the efficiency of SAM and SVM techniques for burned area detection. Based on the experiments in that study, both SAM and SVM methods was used as a useful tool to directly detect the burned area from the landsat TM image. In contrasting the kappa value for both training and assessing data sets, the difference in accuracy was less than 0.3 which indicates that both SAM and SVM was achieved very stable results in burned area prediction.

Giglio *et al.* [6] have presented an automated method for mapping burned areas using 500-m MODIS imagery coupled with 1km MODIS active fire observations. The algorithm applied dynamic thresholds to composite imagery generated from a burn-sensitive vegetation index and a measure of temporal texture. Cumulative active fire maps were used to guide the selection of burned and unburned training samples. An accuracy assessment for three geographically diverse regions (central Siberia, the western United States and southern Africa) was performed using high resolution burned area maps derived from landsat imagery. Mapped burned areas were accurate to within approximately 10% in all regions except the high tree cover sub region of southern Africa, where the MODIS burn maps under estimated the area burned by 41%. They estimated the minimum detectable burn size for reliable detection by their algorithm to be on the order of 120.

Carlà *et al.* [3] have proposed a approach for a multitemporal slicing threshold method aimed at burned area mapping, based on a couple of images both acquired after the fire season and the related performances have been tested. The proposed multitemporal approach showed significative performances that were comparable with those of the single image methods when the NDVI index was considered and very better when the NDII method was applied. The proposed multitemporal approach based on the NDII index results therefore as the best method among the tested slicing threshold methods and this behavior was at a first analysis maintained by changing the adopted multispectral image and the period of acquisition, showing a good robustness of the procedure. Carla *et al.* [3] have presented a multi-criteria approach based on spectral indices, soft computing techniques and a region growing algorithm; theoretically that approach relied on the convergence of partial evidence of burning provided by the indices. Their proposal features several innovative aspects: it was flexible in adapting to a variable number of indices and to missing data; it exploited positive and negative evidence (bipolar information) and it offered different criteria for aggregating partial evidence in order to derive the layers of candidate seeds and candidate region growing boundaries. The study was conducted on a set of landsat TM images, acquired for the year 2003 over Southern Europe and preprocessed with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) processing chain for deriving surface spectral reflectance qi in the TM bands

Wanga *et al.* [23] have evaluated the forest fire detection ability of the HJ sensors. An improved contextual fire detection algorithm for HJ data was proposed. The work presented in that paper provided both qualitative and quantitative evaluations of a simulated HJ forest fire detection and its characteristics. Several general implications were deduced from that work: On the basis of the MODIS contextual algorithm, the fire detection algorithm based on HJ-IRS was established according to the characteristics of HJ-IRS; the fire detection algorithm was tested and evaluated using the HJ-CCD and MODIS data and images of the burned area at the same time and region. The results showed that the mean actual deviation of the burned area was 11% and the degree of similarity with the number of HJ-CCD fire pixels was 94%. The mean referenced deviation based on the MODIS fire products was 13% and the degree of similarity with the number of MODIS fire pixels was 89%. Therefore, the improved algorithm was stable and highly reliable; However, the forest fire data used to test and evaluate the algorithm were mainly from Northeast China. The feasibility of the algorithm should be tested at different time intervals and in different regions. The proposed algorithm was similar to a regional fire detection algorithm because the study area was not large enough. The simulation provided an important method for the evaluation of the HJ fire detection algorithm, but does not completely represent the real landscape. The proposed algorithm must therefore be further tested and evaluated using more HJ data.

The main contributions of proposed burnt area identification technique are:

- Burnt area identification is done with the help of IHS transformation and image segmentation. Here, K-means is used for object segmentation and FFNN is used for smoke segments identification.
- For performance evaluation, we have compared proposed with Bayesian approach.

3. Technique for Burning Area Identification Using IHS Transformation and Image Segmentation

The process of identifying the burnt area in proposed technique consists of three steps such as: IHS transformation, object segmentation, identification of smoke area using FFNN and discovering burning areas from the smoke segments using directional analysis. The overall diagram of proposed burning area identification technique is shown in Figure 1.

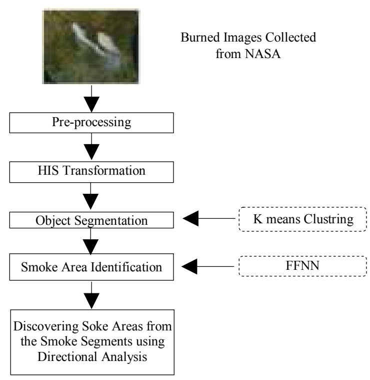

Figure 1. Overall block diagram of burning area identification technique.

Pre-processing steps: The input burning image is firstly converted into RGB to LAB color space. Subsequently, contrasts adjust the L layer of lab image using imadjust function and finally convert back to the RGB colour space.

3.1. IHS Transformation

The Pre-processed burned images cannot be fed directly as the input for the segmentation process. The pre-processed images are subjected to a set of additional pre-processing steps so that, the image gets transformed to be suitable for the further processing. Here, we have used IHS transformation for additional pre-processing step. In the IHS colour coordinate system [4], Intensity (I) refers the total brightness that corresponds to the surface roughness and it is varies from black (0) to white (255), Hue (H) the wavelength contribution and Saturation (S) is its purity [4]. IHS representation is given by follows:

- *I*: Intensity is calculated by following formula:

$$I = \frac{1}{2}(M + m) \tag{1}$$

Where $M = max(R, G, B)$, $m = min(R, G, B)$.

- *S*: Is calculated by following formula:

$$S = M - m \tag{2}$$

- *H*: Is calculated by following formula:

$$H' = \begin{cases} undefined, & if\ C = 0 \\ \frac{G - B}{S} \bmod 6, & if\ M = R \\ \frac{B - R}{S} + 2, & if\ M = G \\ \frac{R - G}{S} + 2, & if\ M = B \end{cases} \qquad H = 60^\circ \times H' \tag{3}$$

3.2. Object Segmentation Using K-Means Clustering

After the transformation of image, we have segmented the input burned image using object segmentation technique based on clustering algorithm. Normally, cluster analysis divides the same dataset into several groups. In this paper, we have used K-means clustering algorithm that divides the burned image dataset into k-groups so that similar data objects belong to the same cluster and different data objects belong to separate cluster. i.e., the burned image is clustered based on *I*, *H* and *S* values into k-cluster using k-means algorithm. The K-means classification groups all the pixels in the burned image into a specified number of classes where each class contains a cluster of pixels. The clustering groups the relevant pixels into one group and then, from the groups, the regions that smoke areas are identified. In the clustering analysis, we are given a burning image dataset $\{b^{(1)}, b^{(2)}, ..., b^{(m)}\}$ and want to group the data into a few clusters. Here, $b^{(i)} \in R^n$ as usual. Finally, this algorithm aims at minimizing an objective function, in this case a squared error function.

The objective function is given by:

$$O^{(i)} = argmin_j \left\| b^{(i)} - c_j \right\|^2 \tag{4}$$

Where $\|b^{(i)}-c_j\|^2$ is a chosen distance measure between a data point $b^{(i)}$ and the cluster center c_j is an indicator of the distance of the *n* data points from their respective cluster centres.

In Algorithm 1, *k* is the number of clusters we want to find and the cluster centroids c_j represent our current guesses for the positions of the centers of the clusters. To initialize the cluster centroids (in step 1), we could choose *k* training examples randomly and set the cluster centroids to be equal to the values of these *k* examples.

Algorithm 1: K-means clustering.

Step 1: *Initialize cluster centroids* $c_1, c_2, ..., c_k \in R^n$ *randomly,*
Step 2: *Repeat until convergence.*
{
For every i, set

$$O^{(i)} = argmin_j \left\| b^{(i)} - c_j \right\|^2$$

For each j, set

$$c_j = \frac{\sum_{i=1}^{m} 1\{O^{(i)} = j\} b^{(i)}}{\sum_{i=1}^{m} 1\{O^{(i)} = j\}} \tag{5}$$

}

3.3. Identification of Smoke Area Using Feed-Forward Neural Network

In this section, we have explained identification steps, to identify smoke area from the segmented regions. For this purpose, we use FFNN for detect smoke area from the segmented regions. First, we calculate twelve features like as entropy, mean based on HSL and RGB colour space. This process is done for segments and then one feature matrix is formed as shown in Figure 2. The entropy (*H*) and mean (μ) are calculated as follows:

$$Entropy,\ H = \sum_{j=1}^{n} P(p_i) log_2 \left(\frac{1}{P(p_i)} \right) \tag{6}$$

Where $P(p_i)$ is the probability mass function of outcomes of pixel p_i.

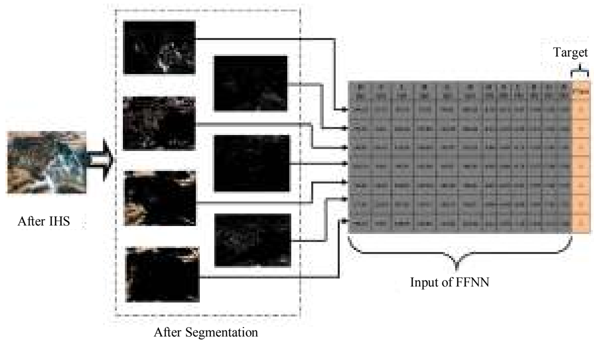

Figure 2. Input and target output of FFNN.

$$Mean,\ \mu = \frac{1}{n} \sum_{i=1}^{n} p_i \tag{7}$$

Where, p_i is the pixel of m^{th} segment.

From the feature matrix, we have chosen input and output parameters of neural network for training and testing purpose. How will choose input and output parameters of neural network for proposed technique in shown in Figure 2. Here, we have given twelve features based on the Equations 6 and 7 for input and target class of corresponding segments for output. For output target, we have taken like as smoke region=2 and other region=1.

The neural network is classified into following major steps. The important steps involved in neural network are as follows:

- To the output layer the output of the activation function $f(ln(H_i))$ is then broadcast all of the neurons:

$$(C_1)output = \eta_k + \sum_{n=1}^{N} W_{2nl} C_1(n) \quad (8)$$

Where η_i and η_k are the biases in the hidden layer and the output layer.

- Compute the error between the desired output, $(C_1)target$ and the output $(C_k)output$ produced by the FFNN, this is given by:

$$E_v = (C_1)target - (C_1)output \quad (9)$$

In Equation 9 $(C_1)target$ is the target output and $(C_k)output$ is the network output.

3.4. Discovering Burning Areas from the Smoke Segments Using Directional Analysis

From the FFNN, the smokes with red regions are obtained. In our NASA image (Database) consist of smoke and red regions as shown in Figure 5. The red region represents burning area. The main target of this section is to identify the red region (burning area) from the smoke segments in shown in Figure 3.

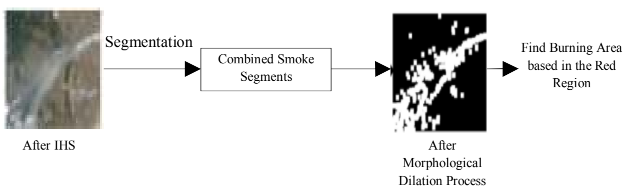

Figure 3. Discovering burning areas from the smoke segments using directional analysis.

We have involved following steps for this purpose:

- After identified class, we have combined all smoke segments from the segmentation regions.
- Subsequently, the morphological dilation process is used for red region identification purpose. For this process, firstly, the smoke segments are converted into binary image and then apply the dilation process. Using this dilation process, we have dilated the smoke areas. The morphological dilation process is done by following formula:

$$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \phi\}$$

Where $\hat{B}$ is the reflection of the structuring element B, it is the set of the pixel location z. where the reflected structuring element overlaps with foreground pixels in A when translated to z.

- The smoke segments are converted into HSL colour space. From the H layer, we have identified red region by following process:

$$H = \begin{cases} (0-15)\, and\, (345-360), & should\ be\ \ red\ region \\ otherwise, & non-red\ region \end{cases}$$

4. Results and Discussion

This section presents the results obtained from the experimentation and its detailed discussion about the results. The proposed approach of burnt area identification is experimented with the NASA satellite dataset and the result is evaluated with the sensitivity, specificity and accuracy.

4.1. Experimental Setup and Dataset Description

The proposed approach is performed in a windows machine having configurations Intel (*R*) Core i5 processor, 3.20 GHz, 4 GB RAM and the operation system platform is Microsoft Wnidow7 Professional. We have used mat lab latest version (7.12) for this proposed method. We established five study places (northern California, central Idaho) in USA from NASA website [14] that covers only smoking based burning conditions. The uses of these different study sites enhance the ability to extrapolate and generalize our findings. The downloaded satellite image obtained will have multispectral (*R*, *G*, *B*, NIR) bands and these images converted to TIFF format. This is done using Multispec32 which is a freeware multispectral image data analysis system. Figure 4 shows some of the sample burnt area satellite images.

Figure 4. Sample dataset images of proposed technique.

4.2. Evaluation Metrics

The evaluation of proposed technique in different NASA satellite images are carried out using the following metrics as suggested by below equations:

$$Sensitivity = \frac{number\ of\ true\ positives}{number\ of\ true\ positives + number\ of\ false\ negatives} \quad (10)$$

$$Specificity = \frac{number\ of\ true\ negatives}{number\ of\ true\ negatives + number\ of\ false\ positives} \quad (11)$$

$$Accuracy = \frac{number\ of\ true\ positives + number\ of\ true\ negatives}{number\ of\ true\ positives + false\ negatives + true\ negatives + false\ positives} \quad (12)$$

4.3. Experimental Results

The proposed technique is designed for burnt area identification in satellite burnt satellite images. The obtained experimental results from the proposed technique are given in Figures 5, 6, 7, 8, 9 and 10. Figure 5 represents input satellite image and Figure 6 shows pre-processed image. Pre-processed means IHS transformation. Segmentation results are shown in Figure 7. Figure 8 shows combined all smoke region. Figure 9 represents morphological dilation applied image and finally Figure 10 shows red region (burnt area) representation.

Figure 5. Original NASA burnt image.

Figure 6. After IHS.

Figure 7. After segmentation using K-means.

Figure 8. Combined all smoke regions.

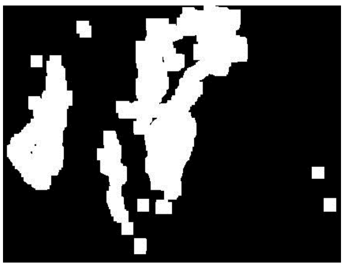

Figure 9. After morphological dilation process.

Figure 10. Red region identified (represented by yellow shade).

4.4. Performance Evaluation

In this section, we describe the performance evaluation and comparative analysis of proposed approach for existing techniques. Here, we compare proposed approach with Bayesian classifier for burning area identification. The performance analysis has been made by plotting the graphs of evaluation metrics such as sensitivity, specificity and the accuracy as shown in Figures 11, 12 and 13. By analyzing the plotted graph, the performance of the proposed technique has significantly improved the burning area detection compared with Bayesian classifier. Particularly, in Figure 11 (5.jpg), the proposed technique is achieved the accuracy of about 99.50% where, the existing technique (Bayesian classifier) has achieved only 99.45%. In Figure 11 (8.jpg), the proposed approach is achieved the accuracy of about 99.62% which is high compared with existing approach only 99.45%. But, the overall accuracy (average accuracy range of five images) is obtained about 2.6%, which shows that the overall prediction performance was good in our proposed approach. In Figure 12, the specificity is achieved 99.58% for first image (5.jpg), where, the existing technique has achieved only 99.53%. In the Figure 13, we have achieved better value and in terms of sensitivity, the proposed algorithm ensured that the performance is considerably improved for various images. Totally, experimental results shows that the proposed approach is obtained better results for burning area identification compare with existing approach.

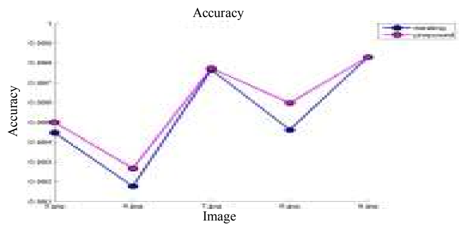

Figure 11. Accuracy graph of proposed and bayesian classifier (images vs. accuracy).

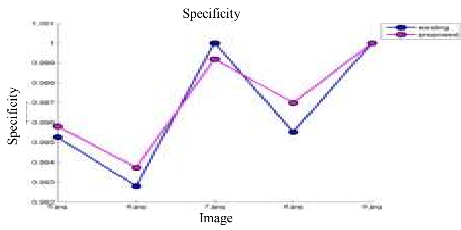

Figure 12. Specificity graph of proposed and bayesian classifier (images vs. specificity).

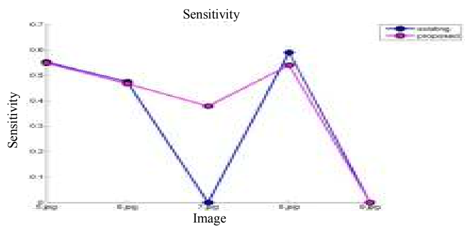

Figure 13. Sensitivity graph of proposed and bayesian classifier (images vs. sensitivity).

5. Conclusions

In this paper, we have presented a technique for burning area identification using IHS transformation and image segmentation. The proposed technique consists of four steps such as: IHS transformation, object segmentation, identification of smoke area using FFNN and discovering burning areas from the smoke segments. Here, satellite image collected from NASA is utilized for the experimental study of the proposed research. The images obtained from the NASA is given to HIS transformation that convert the RGB image into intensity, hue, saturation transformed image. After the transformation of image, object segmentation technique is done based on K-means clustering algorithm. Subsequently, FFNN is used for identification of smoke area from the segments. After identifying the smoke segment, the burning area is identified through directional analysis. The proposed burnt area identification technique is analyzed with the help of sensitivity, specificity and the accuracy. Finally, in the performance evaluation, the proposed technique is achieved the overall accuracy 2.6%, which is better than the existing approach.

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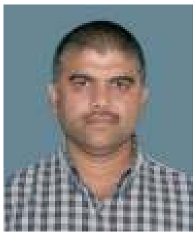

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