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EMPIRICAL DECOMPOSED KERNEL HOUGH FEATURE TRANSFORM BASED VECTOR AUTOREGRESSIVE BAGGING ENSEMBLE FOR FOREST FIRE DETECTION

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ABSTRACT

Background: *Forest fire detection attains a great attention due to the frequent threat from fire to both economic properties and public safety. Automatic fire detection from video data in real-time based on a combination of features is still faced the challenging one.* ***Methods:*** *The paper presents the time series forecasting technique called Empirical Decomposed Hough Feature Transform Based Vector Autoregressive Bagging Ensemble (EDHFT-VABE) for improving the accuracy of fire detection with minimum time. The video is taken from the dataset for fire detection with higher accuracy. EDHFT-VABE technique includes three major processes namely keyframe extraction, feature extraction, and classification. Initially, the input video is divided into a number of frames and finds the keyframes using the empirical mode decomposition approach. Then, the local features and global features are extracted from the given keyframe using generalized kernel Hough transform. Finally, the classification is performed using the time series model called Stochastic Vector Autoregressive Bagging Ensemble for identifying the fires in the given video frames by analyzing the extracted features using Ruzicka similarity. EDHFT-VABE technique is experimented using a video dataset and the final results show that the presented EDHFT-VABE achieves higher fire detection accuracy with minimum time and false-positive rate.* ***Results:*** *The experimental result evident that EDHFT-VABE technique increases fire detection accuracy by 10% and minimizes false-positive rate by 52%.* ***Conclusion:*** *Our EDHFT-VABE technique achieves accurate automatic forest fire-alarm systems with improved fire detection accuracy and lesser time as well as a false-positive rate.*

KEY WORDS
Forest fire detection, empirical mode decomposition feature extraction, generalized kernel Hough transform, Stochastic Vector Autoregressive Bagging Ensemble

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INTRODUCTION

Forest Fire is destructive natural or man-made disaster and it is the most harmful natural hazard affecting everyday life. A hybrid Adaboost-MLP (multi-layer perceptron) model was introduced in [1] to efficiently predict a fire with higher accuracy. However, the time consumption of fire detection was not minimized. A deep CNN model was developed in [2] for accurate fire detection from the video. However, the designed model failed to use the fire detection methods with the detailed experiments of the quantitative analysis.
The rest of paper is organized as follows: Section 2 describes the proposed EDHFT-VABE in a detailed manner. In Section 3, an experimental evaluation of proposed methods and existing methods are presented. In section 4, the quantitative results and discussions are presented with different metrics. Conclusions are drawn in Section 5.

A Robust AdaBoost (RAB) classifier was developed in [3] to enhance the classification accuracy of fire smoke detection. But the time series model was not applied for improving the accuracy of fire detection. A CNN was developed in [4] for forest fire image recognition by extracting the fire features. But the designed CNN failed to minimize the time consumption taken for forest fire detection. An efficient rule-based forest fire detection technique was introduced in [5]. Though the technique achieves a higher detection rate, the multiple fire feature extraction was not performed to minimize the time complexity. In order to minimize the computation time, a multi-feature fusion of flame method was proposed in [6]. The method uses the SVM classifier for fire detection but the false positives were not minimized. ICA K-medoids-based fire region detection method was introduced in [7] based on the spatiotemporal visual features. But the designed method failed to use different types of local and global features for fire region detection. An early fire detection framework was developed in [8] with fine-tuned convolutional neural networks for CCTV surveillance cameras to identify the fire in different indoor and outdoor environments. However, the framework failed to achieve higher accuracy and minimum false alarms. A spatial prediction method using CNN was developed in [9] for forest fire susceptibility. However, the method was not improving the forest fire prediction with minimum time consumption. Cost-effective fire detection was performed in [10][21] using CNN architecture for surveillance videos. But the designed architecture has higher false alarms in the fire detection. A CNN based system was introduced in [11] for identifying fire detection from videos. But early forest fire detection was not performed with higher accuracy and minimum time. A CNN inspired by Mobile Network was developed in [12] for fire detection with the color features. But it failed to analyze the multiple features for accurate fire detection. A Faster Region-based Convolutional Neural Network (R-CNN) was introduced in [13] to identify the suspected regions of fire and of non-fire based on their spatial features. However, the accuracy rate of fire frame detection was not improved. A Gaussian Mixture Model-based background subtraction was developed in [14] to extract the moving objects from a video stream. A sequential Monte Carlo estimation approach of time-varying frequency was developed in [15] using particle filter (PF). But, the error rate was not minimized using sequential Monte Carlo estimation approach. A spatial fuzzy C-means clustering (SpFCM) method was introduced in [16] for fire detection. The designed method failed to use the multiple Spatio-temporal fire features for improving the accuracy of fire detection. The multi-feature based fire detection was performed in [17] for minimizing the error rate. But the false positive rate was not minimized using the designed approach. A vision-based forest fire detection method was introduced in [18] based on color and motion analysis. The designed method failed to use the efficient machine learning technique to improve the performance of forest fire detection and decrease the false positive rate. A K-medoids Clustering was designed in [19] to detect fire frames according to color space using a particle swarm optimization approach. A new video-based fire detection algorithm was developed in [20] based on a rule-based method using RGB and HSV color space.

The aim of the work is to improve the accuracy of forest fire detection; an EDHFT-VABE technique is introduced. This contribution is achieved by extracting the keyframes and learning the multiple local and global features from the input frames. The Stochastic Vector Autoregressive Bagging Ensemble is applied for identifying the forest fires by analyzing the extracted fire features with testing features. The Ruzicka similarity coefficient is used for matching the feature vectors. Based on the similarity value, the fired frames are correctly identified. To minimize the false positive rate of forest fire detection, the EDHFT-VABE technique uses Bagging Ensemble technique by applying the voting scheme. The majority votes of the input samples are taken as final classification results from the weak learner. To minimize the forest fire detection time, the EDHFT-VABE uses the empirical mode decomposition approach to divide the video into the number of key frames.

METHODS

An EDHFT-VABE technique is introduced for detecting fire flame in surveillance video scenes in an early stage. Due to the climatic condition changes, the accurate detection of fire flames is a severe problem in the forest area. These problems are overcome by EDHFT-VABE technique to improve accurate fire detection by extracting the multiple fire features.

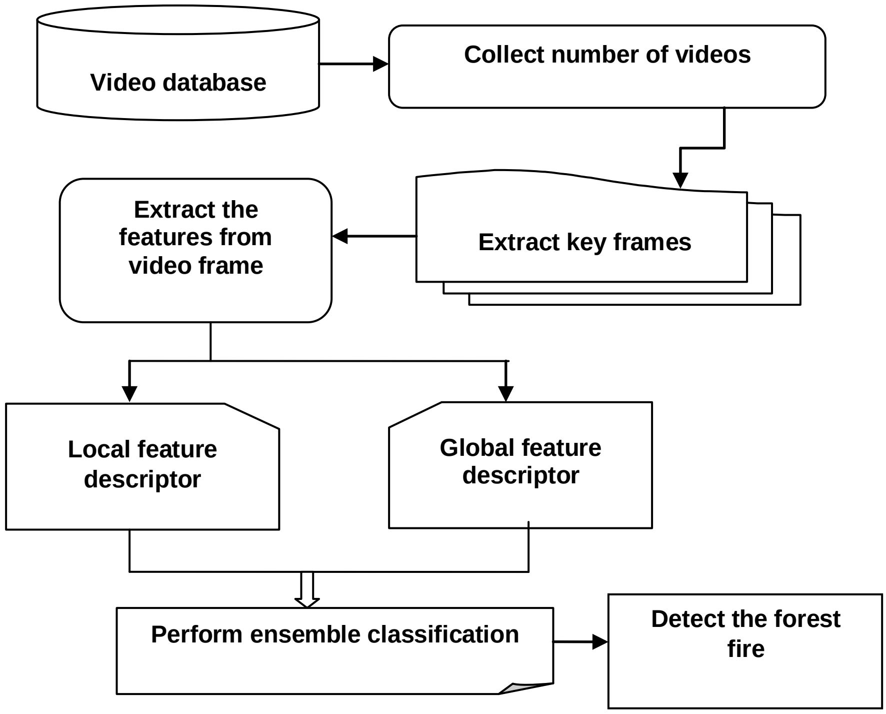

Fig. 1: Architecture of the proposed EDHFT-VABE technique

The architecture of the EDHFT-VABE technique is shown in [Fig. 1]. Initially, the videos are collected from the database. Forest fire detection is carried out with number of video frames $V_i = F_1, F_2, \ldots, F_m$. Then, key frames are extracted to perform fire detection. With the key frames, the local feature descriptor such as color, shape, texture and global feature descriptors like, spatiotemporal energy color, Spatial wavelet energy, temporal analysis, Motion analysis are extracted to improve the classification performance with minimum time. At last, the ensemble classification is performed using the time series model with the extracted features to find the fired region in the given video frame. These three processes of the EDHFT-VABE technique are described in the following section.

Empirical mode decomposition based keyframe extraction

The first process in EDHFT-VABE technique is to extract the video frames from the given input video. With development of multimedia information technology, efficient access to video is a difficult task. Therefore, Empirical Mode Decomposition (EMD)[22][23] approach is applied to divide the total video into number of frames and accurately find key frames for fire detection with minimum time. Let us consider number of videos from dataset $V_1, V_2, V_3, \ldots V_n \in D$. For each video, the multiple video frames $F_1, F_2, \ldots, F_m$ are obtained based on similarity measure. The similarity between frames are measured as follows,

$$Sim\left(F_i, F_j\right) = \sqrt{\sum_{i,j=1}^{m}\left(F_i - F_j\right)^2} \quad (1)$$

From (1), $Sim\left(F_i, F_j\right)$ denotes a similarity between i^{th} frame (F_i) and j^{th} frame (F_j) . The similarity distance between two frames is calculated to find the adjacent frames. The minimum distance similarity is taken as next successive frame. Key frames are extracted by finding each local minimum frame pixels and maxima pixels. With minimum and maximum ranges, the mean frame pixels are identified. By using Empirical mode approach, a center value of minimum and maximum is set as a mean. From the calculated mean, the standard deviation is calculated to find key frames for fire detection.

$$S = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(F_i - m_n)} \quad (2)$$

Where, S indicates standard deviation, m_n denotes a mean, F_i denotes a frame, 'm' denotes number of video frames. Then threshold is set to identify the keyframes. Based on the above-said process, all the keyframes are extracted and it used for further processing to minimize the time consumption. The algorithmic process of the step by step process of keyframe extraction is given below,

\\ Algorithm 1 Empirical Mode Decomposition based keyframe extraction Input: Dataset D, Videos $\boldsymbol{V_1, V_2, V_3, \ldots V_n}$ Output: Keyframe extraction
Begin 1. For each video $\boldsymbol{V_i}$ 2. Extract multiple frames $\boldsymbol{F_1, F_2, \ldots, F_m}$ 3. For each $\boldsymbol{F_i}$ 4. Measure distance similarity $\boldsymbol{Sim\left(F_i, F_j\right)}$ 5. Compute the deviation '$\boldsymbol{S}$' 6. If ($\boldsymbol{S < S_{th}}$) then 7. Select the keyframes 8. End if 9. End for 10. End for End

Algorithm 1 describes the Empirical Mode Decomposition (EMD) approach to extract the keyframes for minimizing the forest fire detection time. First, the number of consecutive frames is extracted from the video using a similarity distance measure. Among the frames, the keyframes are extracted based on the mean and deviation. A threshold is set for selecting the keyframes. If the deviation is lesser than the threshold, then the first image of that pair is taken as keyframe. The process is stopped when the frame list is empty.

Generalized kernel hough transform-based feature extraction

After extracting the keyframes, feature extraction is carried out to extract the two different descriptors such as local feature descriptors like color, shape, texture and high-level feature descriptors like spatiotemporal energy color, Spatial wavelet energy, temporal analysis, motion analysis. The Generalized kernel Hough transforms is applied to extract the features from given video frames. Generalized kernel Hough transforms is a feature extraction technique used in image analysis to find fire from the video frame with minimum time. The input frame is taken in the two-dimensional space (x_a, y_a) and it transformed into a single point in the parameter space (φ, θ). Then the transformation from two-dimensional space into the parameter space is given below,

$$\varphi = x_a \cos(\theta) + y_a \sin(\theta) \quad (3)$$

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Where, φ is the distance from the origin to the closest point on the straight line, θ is an angle between the 'x_a' axis and the line connecting origin with that closest point. Followed by, the distance from the center to the object edge is measured to find the shape. The distance between the origin and the edge of the object is expressed using Gaussian kernel.

$$d = \sqrt{(u_2 - u_1)^2 - (v_2 - v_1)^2} \quad (4)$$

$$K = e^{(-\vartheta\, d^2)} \quad (5)$$

$$\vartheta = \frac{0.5}{\sigma^2} \quad (6)$$

Where, d indicates the distance, the point (u_1, v_1) is the origin i.e. location of the center of the object $(0,0)$, (u_2, v_2) denotes an edge of the object, K denotes a Gaussian kernel, is the deviation. From which, each point on the perfect shape of the boundary is extracted from the given video frame. For accurate fire detection, color is a useful feature that measures the color distribution of image. The color features are extracted from the input by converting the RGB image into HSV (hue, saturation, value) color spaces. For each block, a color probability feature is calculated by averaging the color probability of each pixel.

$$C = \frac{1}{N}\sum_{i,j} p_C(i,j) \quad (7)$$

In (7), C represents the color feature, $\sum_{i,j} p_C(i,j)$ denotes averaging the color probability of each pixel intensity, N denotes a total number of pixels. The texture features are calculated based on the correlation of pixel intensity using mean and standard deviation.

$$T = \sum_i \sum_j \frac{1}{D^2}\left((p-\mu)(q-\mu)\right) \quad (8)$$

Where, T denotes a correlation between the pixel p and its neighboring pixels q based on the mean $(\mu)$and the deviation D. After identifying the local feature descriptor, then the global feature is extracted. The Spatio Temporal Energy Color is defined as given below.

$$STEn_i(\theta, T) = \frac{\sum(p,q) \in InF_i\; wc(p,q)}{\sum(p,q) \in InF_i\; WC(p,q)} \quad (9)$$

$$wc\,(p,q) = H(p,q) + L(p,q) + D(p,q) \quad (10)$$

$$WC(p,q) = D(p,q) \quad (11)$$

Where, ' $STEn_i$denotes a spatiotemporal energy color analysis is performed based on the wavelet coefficient ($wc\,(p,q)$) of the horizontal $H(p,q)$, vertical $L(p,qv)$ and diagonal directions $D(p,q)$, 'θ' and 'T ' denotes a direction and magnitude, $WC(p,q)$ denotes an overall wavelet coefficient that refers to the diagonal parts $D(p,q)$. Spatial wavelet energy at each pixel is powerful fire feature is measured by following formula,

$$SE\,(p,q) = hl\,(p,q)^2 + lh\,(p,q)^2 + hh\,(p,q)^2 \quad (12)$$

Where, $SE\,(p,q)$ denotes spatial energy at each pixel (p,q) , hl denotes a high-low frequency subband of the wavelet coefficient, lh denotes a low-high frequency subband, hh denotes a high-high frequency subband. For each subband, the spatial wavelet energy is calculated as the average of the energy of the pixels in the band.

$$E_b = \frac{1}{N}\sum E(p,q) \quad (13)$$

Where, E_b denotes the energy of the band, $E(p,q)$ denotes an energy of band in a particular pixel intensity, N denotes the number of pixels in a band.

Temporal analysis

Temporal analysis is applied to identify the flickering effect. To measure the effect of flickering in a pixel, the number of transitions from fire candidate i.e. moving fire colored pixel, to the non-fire colored pixel. Therefore, the flickering effect for a particular pixel is mathematically expressed as a function of the number of transitions ‘$v(p,q)$’ which is mathematically calculated as follows,

$$f(p,q) = 2^{v(p,q)} - 1 \qquad (14)$$

Where, $f(p,q)$ denotes a flickering effect of a particular pixel. The overall flicker effect is estimated as the average of individual flickering contributions of the pixels in the block.

Motion analysis

The motion analysis is used for detecting the fire regions is the movement of fire pixels in successive frames. In order to detect the foreground objects, the frame difference map is estimated as follows,

$$F_{map} = |F_i - F_{i-1}| > th \qquad (15)$$

From (15), F_{map} denotes a frame difference map, F_i denotes a current frame, F_{i-1}denotes a consecutive frame. The pixels which are not moving for a long time in the next consecutive frames are considered a reliable background. The pixels which moving from one frame to another is called foreground (i.e. movement of the object). From the motion analysis, the moving pixels of the objects are identified. Finally, local and global features are combined to perform forest fire detection. Algorithm 2 describes the generalized kernel Hough transform based feature extraction. Initially, the Hough transform is employed to extract different features and finally combined all the features for classification. The feature extraction process minimizes fire detection time.

Input: Number of keyframes $KF_1, KF_2, \dots. KF_n$
Output: Extract the features

1: Begin
2: For each keyframe ‘KF’
3: Measure shape analysis using Hough transformation
4: Measure color probability feature ‘C’
5: Measure texture feature ‘T’
6: Calculate Spatio-temporal Energy Color $STEn_i(\theta, T)$
7: Calculate Spatial wavelet energy $SE(p,q)$
8: Calculate Flickering features $f(p,q)$
9: Measure the motion analysis using F_{map}
10: Obtain combined features
10: End for
11: End

Algorithm 2 Generalized kernel Hough transform based feature extraction

Stochastic bayesian vector autoregressive bagging ensemble-based classifications

Finally, the classification is performed using Stochastic Vector Autoregressive Bagging Ensemble (SVABE) technique with the help of a time series model. The Stochastic vector auto regression is the time series model that uses extracted features as input to predict the value at the next time step. The bagging ensemble is the machine learning algorithm designed to improve the accuracy of classification with the help of stochastic vector auto regression. In the SVABE technique, stochastic is a general method for constructing the classifiers based on combining random numbers of weak components and provides accurate classification results and minimizes the error. The ensemble technique is to convert the weak classifier into a strong one by applying the voting scheme.
[Fig. 2] shows the block diagram of SVABE technique. SBVABE uses a set of extracted features (EF_i) as input over the sample period ($t = 1,2, \dots v$). The features are collected in a vector ‘A’ in the form of a

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matrix. The Stochastic Bayesian Vector Autoregressive model acts as a weak learner to analyze the extracted features and classifies the fire in the given video frame.

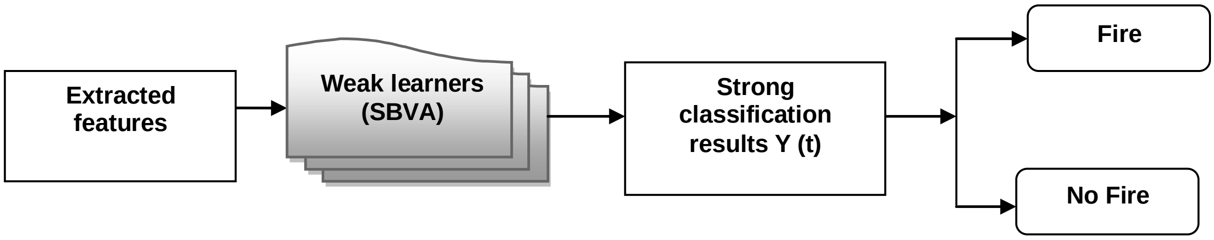

Fig. 2: Stochastic Vector Autoregressive Bagging Ensemble techniques

$$f(t) = b + \sum_{i=1}^{c} A\ f(t-i) + \gamma_t \qquad (16)$$

Where, the observation $f(t-i)$ is called the i-the lag of $f(t)$, $f(t)$ indicates the frame at a time't', b denotes a constant, γ_t is a vector of the error term, A denotes an extracted feature vector. Then the regression function analyzes the extracted features with the testing fire features using Ruzicka similarity. The Ruzicka similarity coefficient is used to measure the similarity between the feature vectors such as extracted feature vector 'A' and testing feature vector 'B'. The mathematical formula for calculating the similarity is given below,

$$\beta = \frac{A \cap B}{\sum A + \sum B - A \cap B} \qquad (17)$$

Where, β represents a Ruzicka similarity coefficient, A, B are the two feature vector, $\sum A$ denotes sum of A score, $\sum B$ denotes the sum of B score, '$\cap$'denotes score, denotes a mutual dependence between the two feature vectors. The Ruzicka similarity coefficient (β) provides a value between 0 and 1. Based on the similarity, the regression function uses observations from previous time steps as input to predict the value at the next time. The training and testing fire features are exactly matched, and then the fired frame is correctly detected. Otherwise, there is no possibility of fire in the given frame. The weak learner has some training error hence the performance is minimized. In order to obtain the higher accuracy of fire detection, ensembles technique combines all weak learner to obtain the strong classification as follows,

$$Y(t) = \sum_{k=1}^{M} v_i(t) \qquad (18)$$

Where, $Y(t)$ denotes an output of strong classifier, $v_i(t)$ indicates the weak learner. After combining the weak learner, the voting scheme is applied for accurately detecting the forest fire. The majority votes of the weak learner results are considered as a final strong output as given below,

$$Y(t) = arg \max_{M} \tau(v_i(t)) \qquad (19)$$

From the above (19), τ denotes a majority votes whose decision is known in the M^{th} classifier, '$arg \max_{M}$' denotes argumentation of maximum function which helps to find majority votes of weak learner output. In this way, the fires in given input frames are correctly identified with a minimum false positive rate. The Stochastic Bayesian Vector Autoregressive Bagging Ensemble (SBVABE) algorithm is given below. The regression function analyzes the extracted features with the testing fire features. If these two features are similar, fire is detected in the given input frame.

\\ Algorithm 3 Stochastic Vector Autoregressive Bagging Ensemble Input: Extracted features Output: Improve the fire detection accuracy
1: Begin 2: For each key frame 'KF' with extracted features EF_i 3: Construct 'M' number of weak learners

Analyze the EF_i with testing features $f(t)$
  if $(\beta > th)$ then
    Higher probability of fire
  else
    No probability of fire
  end if
  Combine all weak learner outputs $\sum_{k=1}^{M} v_i(t)$
 For each $v(t)$
  Apply votes 'τ'
  Find majority vote $\arg\max_{M} \tau(v_i(t))$
  Obtain strong classification results $Y(t)$
 End for
End for
End

RESULTS

Results of the EDHFT-VABE technique and existing methods Adaboost-MLP model [1] and DEEP CNN MODEL [2] are implemented using MATLAB with FIRE SENSE database (https://zenodo.org/record/836749). The dataset includes several forest fire videos for conducting the simulation. The collected video frames are used for fire detection.

Qualitative analysis

To conduct simulation, the method uses different numbers of video frames ranging from 25 to 250. Specifically, the state-of-the-art methods, Adaboost-MLP model [1] and deep CNN model [2] and EDHFT-VABE technique have been tested with the FIRESENSE database. The effectiveness of the proposed technique is compared along with the different performance metrics such as fire detection accuracy, false positive rate and fire detection time with the help of tables and graphs.

Performance metrics

Fire detection accuracy (FDA): Fire Detection Accuracy is referred to as a number of frames correctly detected as fire to the total number of frames taken as input. The fire detection accuracy is calculated as follows,

$$FDA = \frac{Number\ of\ F_i\ are\ correctly\ detected}{m} * 100 \qquad (20)$$

Where FDA denotes a fire detection accuracy, F_i denotes the number of frames, m denotes a total number of frames. FDA is measured in terms of percentage (%).

False-positive rate (FPR): It is defined as the ratio of the number of video frames that are incorrectly detected to the total number of video frames. The mathematical formula for calculating the FPR is given below,

$$FPR = \frac{Number\ of\ F_i\ are\ incorrectly\ detected}{m} * 100 \qquad (21)$$

Where, F_i denotes number of frames, denotes a total number of frames. FPR is measured in percentage (%).

Fire detection time (FDT): It is measured as an amount of time taken by the algorithm to detect the fire from the given video frame. It is expressed as follows,

$$FDT = m * t\ (detecting\ fire\ in\ one\ frame) \qquad (22)$$

Where m denotes a total number of frames, t denotes a time taken to identify the frame from a single frame.

Table 1 describes the results of the fire detection accuracy from the input video frames. The numbers of input frames are taken as input in the ranges from 25 to 250. The estimated results show that the accuracy of the EDHFT-VABE technique is improved by 7% as compared to [1] and 12% when compared to [2].

Table 1: Fire detection accuracy

Number of frames	Fire detection accuracy (%)		
	EDHFT-VABE	Existing Adaboost-MLP model	Existing deep CNN model
25	96	88	84
50	90	82	78
75	93	87	83
100	91	86	83
125	92	88	84
150	93	87	83
175	91	86	82
200	93	88	85
225	96	89	84
250	94	86	83

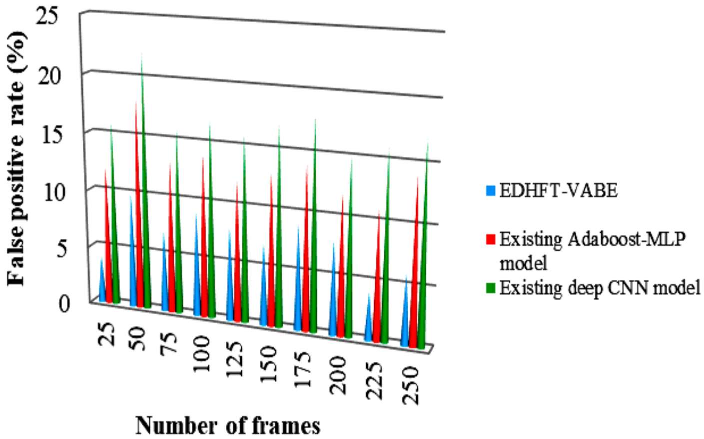

Fig. 3: Result of false-positive rate.

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[Fig. 3] illustrates the false positive rate with number of video frames. The results of EDHFT-VABE technique reduces the false positive rate of frame classification by 46% and 58% when compared to [1] and [2].

Table 2: Fire detection time

Number of frames	Fire detection time (ms)		
	EDHFT-VABE	Existing Adaboost-MLP model	Existing deep CNN model
25	0.575	0.700	1.000
50	0.700	0.900	1.100
75	0.900	1.050	1.200
100	1.000	1.200	1.300
125	1.062	1.250	1.500
150	1.215	1.350	1.575
175	1.312	1.575	1.662
200	1.440	1.700	1.900
225	1.597	1.845	2.070
250	1.800	2.000	2.275

Table 2 shows the fire detection time of the three techniques. The video frames count ranges from 25, 50 …250 and it is given as input. The average of ten results shows that the EDHFT-VABE technique minimizes the 15% of the time for fire detection compared to the Adaboost-MLP model [1] and also minimizes the detection time by 27% as compared to deep CNN MODEL [2].

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From the discussed quantitative and qualitative results, the EDHFT-VABE technique improves the fire detection accuracy with minimum time as well as a false positive rate.

DISCUSSION

In this section, the forest fire detection performance of EDHFT-VABE technique is discussed with metrics namely fire detection accuracy, false positive rate, fire detection time with 250 number of frames taken from FIRESENSE database. Forest fire detection accuracy in [Table 1] provides the results of three different methods. When considering 250 number of features, fire detection accuracy of EDHFT-VABE technique is 94 % whereas the existing method [1] and [2] provides 86% and 83 % of accuracy. This is because, the EDHFT-VABE technique uses the stochastic Vector Autoregressive model for analyzing the extracted features vector with the testing fire feature vector. The Ruzicka similarity is applied for matching the frames with the features. The higher similarity used for identifying the fire and lesser similarity indicates no fire in the given video frame. The ensemble bagging technique improves the classification performance of video frames. This result in EDHFT-VABE provides enhanced performance of fire detection. [Fig. 3] depicts the results of false positive rate. From [Fig. 3], the EDHFT-VABE technique reduces the false positive rate of video frame classification. When Considering 250 number of frames; the EDHFT-VABE technique provides 6% of false positive rate. Whereas, existing [1] and [2] provides 14 % and 17% of false positive rate. The EDHFT-VABE technique utilizes autoregressive model with ensemble technique to analyze feature vectors for providing training and testing features from that particular frame. In addition, the bagging ensemble technique uses the voting scheme for the decision making process. This minimizes the error rate and improves classification accuracy. In [Table 2], the results of fire detection time are provided for existing and proposed methods. At the 25 input frames, fire detection time incurred by the fire detection time is 0.575 ms whereas the fire detection time for the Adaboost-MLP model [1], deep CNN model [2] is 7ms and 1ms. Here, the result shows that the fire detection time of existing methods is comparatively high. Whereas, the fire detection time of the proposed EDHFT-VABE technique is relatively less.

Novelty of the work

On the contrary to existing work, we introduce the Empirical Decomposed Hough Feature Transform Based Vector Autoregressive Bagging Ensemble (EDHFT-VABE) technique with three different processes namely empirical mode decomposition approach, generalized kernel Hough transform, Stochastic Vector Autoregressive Bagging Ensemble for improving the accuracy of forest fire detection. At first, the input video is partitioned to finds the key frames using the empirical mode decomposition approach. Then, the local features and global features are extracted using generalized kernel Hough transforms on the contrary to existing work. After that, Stochastic Vector Autoregressive Bagging Ensemble is utilized for detecting the forest fires through scrutinizing the extracted fire features with testing features. The extracted features are analyzed with Ruzicka similarity. The Ruzicka similarity provides the value between 0 and 1. Based on the similarity value, the fired frames are correctly identified. The EDHFT-VABE technique uses Bagging Ensemble technique by applying the voting scheme to lessen the false positive rate of forest fire detection. The majority votes of the input samples are taken as final classification results from the weak learner. In this way, the fire frames are correctly identified with higher accuracy with minimum false positive rate and fire detection time.

CONCLUSION

Developing a robust fire detection system is a significant process in a video surveillance system. A number of successful methods have been applied to address these issues. The conventional classification algorithms are not sufficient to solve real-world fire detection problems with higher accuracy. An efficient time series model called EDHFT-VABE is introduced to handle a fire detection problem. By modeling both the behavior of the key frame extraction and various Spatio-temporal features as well as the temporal evolution of the pixels' intensity extraction is carried out using generalized kernel Hough transform to obtain higher detection rates while reducing the false positive caused by fire-colored moving objects. With the use of a stochastic vector autoregressive based begging ensemble algorithm, the features are analyzed and classification is performed. As a result, the robustness of the EDHFT-VABE technique is improved hence it improves the fire detection accuracy. Experimental results with videos containing frames showed that the proposed algorithm outperforms the existing fire detection algorithms. The qualitative and quantitative results show that the proposed EDHFT-VABE technique achieves better performance in terms of higher detection accuracy with the minimum false positive rate as well as fire detection time than the state-of-the-art methods. In future, we perform the fire detection using deep learning techniques for achieving more accurate results.

CONFLICT OF INTEREST

There is no conflict of interest.

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