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An Optimum Classifier Model with Fuzzy C-Means for Fire Detection Technology

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ABSTRACT

Flames recognition methodology is most important for completely diminishing the flame losses in different fired environmental conditions. However, there is delayed detection and lower accuracy in the various common detection methods. Thus, optimum image/video fire detection technology is proposed in this paper based on a support vector machine (SVM) with the fuzzy c-mean, discrete wavelet transform (DWT), and gray level co-occurrence matrices (GLCM) feature extraction for the detection of fires. This algorithm has been tested on various fire and non-fire images for classification accuracy. A performance evaluation of the proposed classifier algorithm and existing algorithms is compared, showing that the accuracy and other metrics of the proposed classifier algorithm are higher than other algorithms. Furthermore, simulation results show that the proposed classifier model is improved the forecast detection accuracy of fires.

Keywords: Discrete wavelet transform, feature extraction, fuzzy c-means algorithm, SVM classifier

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INTRODUCTION

Fire detection methods are among the most significant components in surveillance systems that observe buildings and the environment. As part of early warning systems, it is preferable that the system can report the earliest stage of a fire/smoke. Almost all fire/smoke detection systems currently use built-in sensors that depend mainly on the consistency and positional distribution of the sensors. It is necessary that these sensors are distributed densely for a high-precision fire/smoke detection system. In a sensor-based fire/smoke detection system for an outdoor atmosphere, coverage of large areas is not practical due to the requirement of a regular distribution of sensors in closeness. For many years, fire accidents occurred in some locations, including buildings, forests, agriculture, hospitals, aviation, aerospace, and industries. It causes vast losses to all communities and also human life. In order to save production losses and protect against early fire detection, technology is necessary to provide prior information and control the fire in many locations. However, conventional fire detection technologies are unsuitable for large spaces and complex buildings. In preceding fire detection techniques, untrue alarms, missed detections, delays of detection, and other tiny tribulations will arise. To overcome the issues in the previous methods in this paper used optimum deep learning classifier model which is explained in materials and methods section in detail. The objective of proposed model to improves the competency of early fire detection.

Related Works

Many researchers introduced various image fire detection techniques for early effective fire detection to determine the fire hazard from the images/videos. Coppo (2015) proposed an end-to-end fire detection technique by infrared imagers from geostationary satellites for real-time early warning and monitoring. In this method, Metro Second Generation (MSG) SEVIRI and Meteosat Third Generation (MTG) Flexible Combined Imager (FCI) characteristics were simulated. This fire-detection model evaluates the maximum and minimum fire-detectable active region and temperature. This method provides analytical results for MSG-SEVERI and MTG-FCI characteristics, as a consequence, in agreement with literature statistics information. This model can be helpful for early fire detection compared to existing methods from new satellite infrared imagers. The drawback of this system is inaccurate when the system is unaffordable and complex.

Zhang et al. (2018) proposed a wild-land forest fire smoke detection using a faster RCNN to keep away from the complex manual features extraction method in conventional smoke detection techniques. In this scheme, by adding smoke and simulative smoke, synthetic smoke images are produced into the background of forest images to solve the need for training data and eliminate the work of sample labeling. The two synthetic images are trained and tested in the dataset. The simulation results for simulative smoke are the superior choices in the aspect of a detection rate, and this model is not sensitive to thin-smoke images. Further, this algorithm's performance may be tested on video frames or forest fire smoke images.

Singh et al. (2018) presented an effective image retrieval algorithm and a nonlinear SVM classifier. First, the Color-Histogram (C-H), Color-Difference Histogram (C-DH), and Orthogonal Combination-Local Binary Patterns (OC-LBP) features are combined. Then the performances of the three descriptors are analyzed, combined, and individually. Detailed simulation results reveal that the C-H + C-DH+OC-LBP combined algorithm achieved the highest flame detection rate. Also, the nonlinear SVM classifier is more effective than linear SVM and RBF kernels. Moreover, this combined algorithm provides good accuracy for all training datasets using pre-computed square-chord kernel values.

Hou et al. (2019) demonstrated an anomaly fire-detection algorithm for Internet-of-Thing (IoT) applications working environment based on deep learning from fire-smoke detection and video/image personnel detection. The results of fire/smoke detection and multi-stream Convolution Neural Network (ms-CNN) based vision monitoring video/image personnel detection algorithms have excellent detection compared to other methods. However, the drawbacks of this system are multiple gestures visible in the detected image due to people's movement and the difficulty of abnormal detection due to the uncertainty of fire-smoke increases (Scholkopf & Smola, 2018; Schölkopf et al., 2001).

Peng et al. (2019) proposed a video/image smoke-detection algorithm with a deep learning model and effective hand-designed features. In this algorithm, the initially suspected smoke area is extracted using a manual design approach, and then images are classified using an optimized SqueezeNet network (Elaiyaraja et al., 2015; Elaiyaraja et al., 2022). This method achieves quick and accurate smoke detection through real-time monitoring of the forest smoke environment.

Li et al. (2020) demonstrated CNN-based object detection algorithms such as R–FCN, Faster-RCNN, YOLO v3, and SSD for image/video fire detection algorithms. A comparison of various objection detection techniques illustrates that object-detection CNNs algorithms achieve higher performance than other fire detection methods. Particularly, the average precision of the YOLO v3 algorithm is higher than the other algorithms; the detection speed reaches 28 frames per second (FPS) and also has the strongest robustness (Cristianini & Shawe-Taylor, 2000; Dunnings & Breckon, 2018).

Muhammad et al. (2018) proposed an early image/video fire detection framework with fine CNN for effective disaster management. The dynamic channel selection algorithm is implemented in this method for cameras based on cognitive radio networks (CRNs), ensuring reliable data broadcasting. This fire detection scheme provides higher accuracy (94.39%) than state-of-the-art methods. Moreover, this algorithm improves the accuracy value of fire detection with minimum false alarms Escalera et al., 2009; Esfahlani, 2019; Fan et al., 2005; Filizzola et al., 2016; Fürnkranz, 2002).

Fire-detection methodology based on video frames can avoid many errors in traditional algorithms and detect fires. The Rough Set (RS) theory with an SVM classifier is introduced to detect fires and gives fire alert warnings (Huang et al., 2020). RS is used in this method as the front-end system yields improved performance. In addition, the recognition efficiency is improved, and the recognition time is reduced in this algorithm. The experimental result reveals that the RS-SVM optimum classifier algorithm yields a fast recognition speed, higher recognition rate, a wide range of applications, and excellent robustness (Garcia-Jimenez et al., 2017; Genovese et al., 2011; Gottuk et al., 2006).

Seydi et al. (2022) proposed Fire-Net (deep-CNN) to detect active forest fires in different area. This method provides higher accuracy and sensitivity compared to other common machine learning algorithms. But due to level of active fires in small region, this algorithm could not detect active fires (Hackner et al., 2016; Hastie et al., 2009; Jia et al., 2016; Kapil et al., 2016; Kecman et al., 2005; Koltunov et al., 2016).

Many authors are proposed several of machine and deep learning-based algorithm along with suitable technique such as feature extraction, segmentation etc. for image/video fire detection. All existing algorithms have less accuracy, low miss detection rate for small regions (Sharma et al., 2017; Ansari & Ghrera, 2017; Ansari & Ghrera, 2018; Ansari et al., 2016; Ansari et al., 2018; Chen et al., 2017). In the need the further improvement for complex situations in this paper optimum SVM based classifier model is proposed for effective and early fire detection (Li, 2009; Lin et al., 2018; López-García et al., 2022; Mallat, 1989).

MATERIALS AND METHODS

The detailed process of the proposed flow diagram of the Optimum SVM Based Classifier Model is shown in Figure 1.

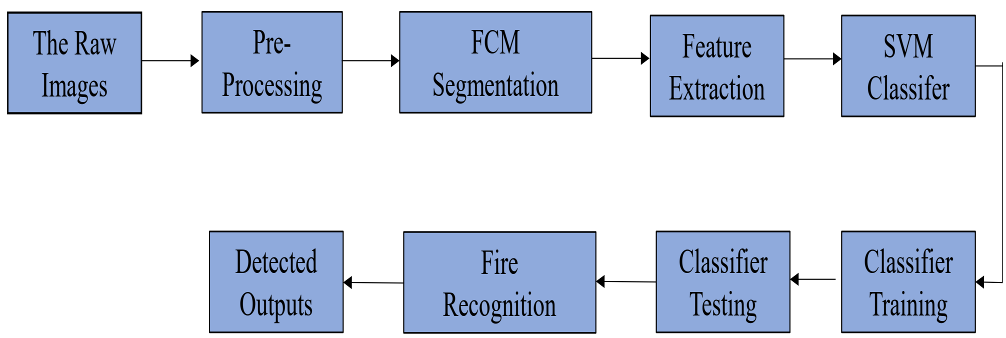


Figure 1. Flow diagram of proposed optimum SVM-based classifier model

The algorithm steps of the proposed optimum classifier model are as follows:

Step 1: Read the raw images, which consist of 150 training images and 50 testing image sets. In the training set, 106 images are fired images, and 44 are non-fired images; in the testing set, 30 are fired images, and 20 are non-fired images.

Step 2: Pre-processing

The image is preliminarily analyzed through the Pre-processing module. This module consists of image resizing, gray conversion, and image enhancement.

The algorithm steps of pre-processing are as follows:

Step 2.1: Image Resize: Here, the input raw images (M × N) are resized to 256 × 256.

Step 2.2: Gray Conversion: Converts true color image pixel values to grayscale pixel values by evaluating the optimum scaled sum of the components of Red (R), Green (G), and Blue (B): 0.2989 R + 0.5870 G + 0.1140 B.

Step 2.3: Image Enhancement: In this step, the quality of the gray converted image is enhanced to the maximum level.

Step 3: Fuzzy C-Mean (FCM) Segmentation

The algorithm steps of the FCM segmentation process are as follows:

Step 3.1: Convert matrix to intensity image

Step 3.2: Computes a global image threshold using Otsu's method.

The global image threshold σ_B^2 is the maximum of between-class variance values and is expressed in Equation 1:

$$\sigma_B^2 = (k_1^*, k_2^*) = {}_{1 \le k_1 < k_2 < L}^{max}\, \sigma_B^2 = (k_1, k_2) \tag{1}$$

Step 3.3: Convert an intensity image into a binary image using global image threshold value σ_B^2.

Step 3.4: Using a three-class fuzzy c-means (Fc-M) clustering (Xiong, 2021), outputs the threshold level of an image and binary image. It frequently works again than Otsu's technique, which gives an image a smaller or larger threshold outputs value. For example, in a Switch of cutoff position, one's (1's) indicates a slice between the middle and large class, and zeros (0's) indicate a slice between the small and middle classes.

The Fc-M algorithm divides a finite group of n elements $z=\{z_1,\ldots,z_n\}$ into a group of fuzzy clusters with respect to given rules.

Given a finite group of data, the algorithm returns a list of c cluster centers $c=\{c_1,\ldots,c_n\}$ and a partition matrix $p= p_{ij}€[0,1]$, $i=1,\ldots,n$, $j=1,\ldots,c$, where each element, p_{ij}, tells the degree to which element, z_i, belongs to cluster c_j.

The Fc-M clustering algorithm aims to average and minimize (arg min) an objective function and is expressed in Equation 2:

$$\arg\min_{C} \sum_{i=1}^{n}\sum_{j=1}^{c} p_{ij}^{m}\left\|z_i - c_j\right\|^2$$

Where

$$p_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|z_i - c_j\right\|}{\left\|z_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \tag{2}$$

Step 4: Feature Extraction

In the proposed framework, 11 features are extracted from the segmented image of the dataset using DWT and GLCM to provide high-detail image components with higher resolution (Cohen, 1994; Meyer, 1995; Otsu, 1979). The two-dimensional (2-D) DWT expresses the decomposition of approximation coefficients, cA_j, into approximation coefficients matrix, $cA_{j+1,}$ and detailed coefficients matrices are cH (Horizontal), cV (Vertical), and cD (Diagonal), respectively. The prime elementary decomposition flow step process for 2-D frames/images is shown in Figure 2.

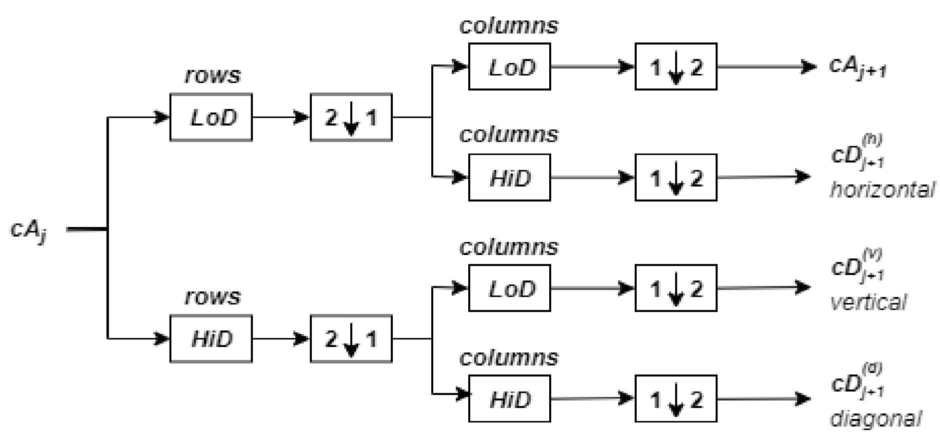


Figure 2. Decomposition Steps for 2-D using DWT

Initially, decomposition is done by setting the approximation coefficients equal to the image f(i,j) [cA0 = x(i,j)] (Zeng et al., 2006).

In this proposed method, seven GLCM features were extracted to characterize the texture of the fire image.

The mathematical model of each feature by following expressions (Equations 3 to 9):

$$\text{Mean: } \mu = \frac{1}{PQ}\sum_{i=0}^{P}\sum_{j=0}^{Q} x(i,j) \tag{3}$$

$$\text{Standard Deviation: } \sigma_{ij} = \sqrt{\frac{1}{PQ}\sum_{i=0}^{P}\sum_{j=0}^{Q}(x(i,j)-\mu)^2} \tag{4}$$

$$\text{Skewness:} \mu_3 = \frac{1}{PQ}\sum_{i=0}^{P}\sum_{j=0}^{Q}(x(i,j)-\mu)^3 \tag{5}$$

$$\text{Kurtosis:} \mu_4 = \frac{1}{PQ}\sum_{i=0}^{P}\sum_{j=0}^{Q}(x(i,j)-\mu)^4 \tag{6}$$

$$\text{Entropy:} \alpha_{ET} = \sum_{i,j} x(i,j)\log_2\left(\frac{1}{x(i,j)}\right) \tag{7}$$

$$\text{Smoothness:} SI = \frac{\mu}{1+\mu} \tag{8}$$

$$\text{Variance: } {\sigma_{ij}}^2 = \frac{1}{PQ}\sum_{i=0}^{P}\sum_{j=0}^{Q}(x(i,j)-\mu)^2 \tag{9}$$

Step 5:

This method uses the optimum SVM classifier model for effective classification with high-dimensional data.

The linear SVM functon is as Equation 10:

$$F(x) = x\beta + a \tag{10}$$

Where: x is an observation

β is the coefficient that characterizes an orthogonal vector to the hyper-plane and a is the biased term.

The dual-formalizations for linear SVM are as Equation 11:

For classes of separable, minimize

$$0.5\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j y_i y_j {x_i}' x_j - \sum_{j=1}^{n} a_i$$

with respect to $a_1,...,a_n$, subject to, $\alpha_j \geq 0$ for all i = 1,...,n.

For classes inseparable, the objective is the same as for separable classes, except for the additional condition $0 \leq a_i \leq C$ for all i = 1,..,n.

The final valued function is as Equation 12:

$$\hat{f}(x) = \sum_{i=1}^{n} \hat{a}_i y_i x' x_i + \hat{b} \tag{12}$$

Where: $\hat{b}$ is the bias estimate, and $\hat{a}_i$ is the ith estimate of the vector $\hat{b}$, i = 1,..., n.
Step 6: Train SVM binary learners.
Step 7: Testing SVM binary learners.
Step 8: Load Trained features, labels, and features extraction.
Step 9: Extract Image Features from the testing and training dataset.
Step 10: Fit a multiclass SVM Classifier.
Step 11: Classify Test Images: Classify the test images using the trained SVM model and features extracted from the test images. Prediction by minimizing the expected misclassification cost (Equation 13):

$$\hat{y} = \underset{y=1,\ldots\ldots K}{\arg\min} \sum_{i=1}^{K} \hat{P}\left(\frac{i}{x}\right) C\left(\frac{y}{i}\right) \tag{13}$$

Where:

- $\hat{y}$ is the predicted classification.
- K is the number of classes.
- $\hat{P}(i/x)$ is the posterior probability of class i for observation x.
- C(y/i) is the cost of classifying an observation as y when its true class is i.

RESULTS AND DISCUSSION

In this paper, the experimental system configuration is as follows:

Processor: Intel Pentium CPU @ 2.30GHz
RAM: 4.00 GB
OS: Windows 10,
Tools: MATLAB (R2020a)
The performance evaluation parameters are expressed in equations from Equations 14 to 18:

$$\text{Accuracy (A)}= \frac{TP+TN}{TP+FP+TN+FN} \tag{14}$$

$$\text{Precision(P)}= \frac{TP}{TP+FP} \tag{15}$$

$$\text{Sensitivity (True Positive Rate)} = \frac{TP}{TP+FN} \tag{16}$$

$$\text{Sensitivity (True Positive Rate)} = \frac{TP}{TP+FN} \tag{17}$$

$$F1= \frac{TP}{TP+\frac{1}{2}(FP+FN)} \tag{18}$$

Where

TP (True Positive) is the number of fire detection samples is accurately recognized
FN (False Negative) is the number of fire detection samples deemed as non-fire
TN (True Negative) is the number of non-fire detection samples judged as non-fire,
and FP (False Positive) is the number of fire detection samples as non-fire.

(a) Original fired image-1

(b) Original non-fired image-2

Figure 3. Original fired and non-fired input image

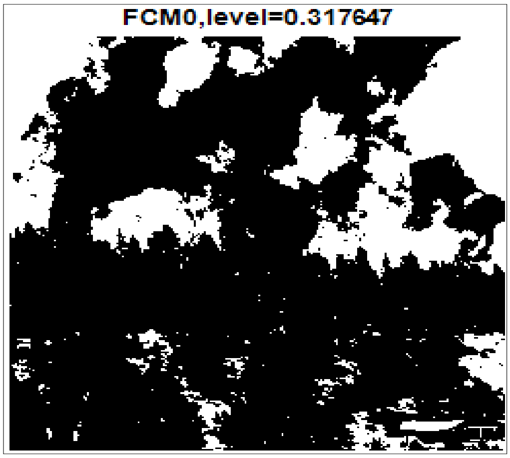
(a) Resize image (256 x 256)

(b) Grayscale image

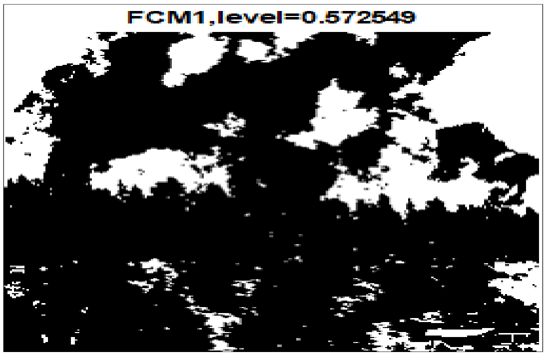
(c) Enhanced-image

Figure 4. Pre-processed images

a) Binary version of enhanced original image-1

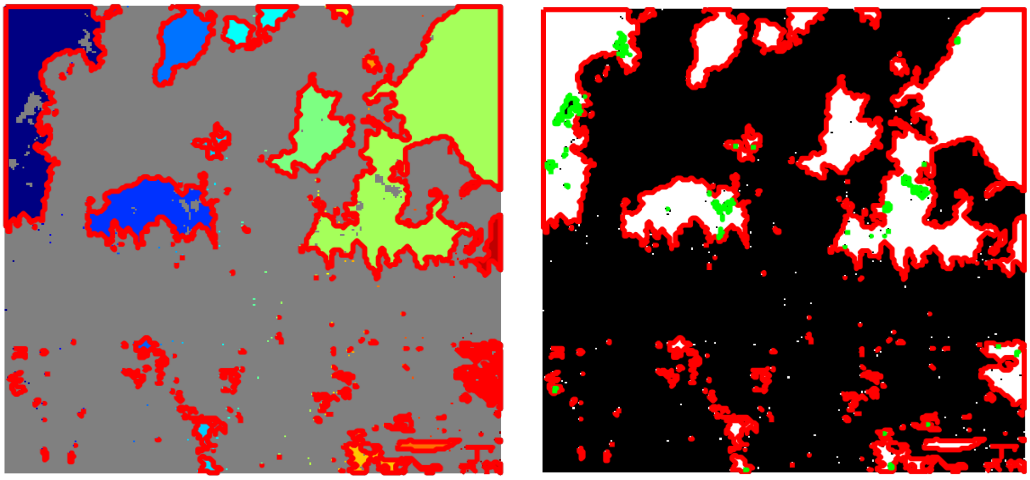


(b) FCM Level-0 segmented portion of image-1



(c) FCM Level-1 segmented portion of image-1

Figure 5. FCM segmentation images



(a) Overlay Region Boundaries of Segmented Image

(b) Object Boundaries and Hole Boundaries of Segmented Image

Figure 6. Boundaries of FCM segmentation images

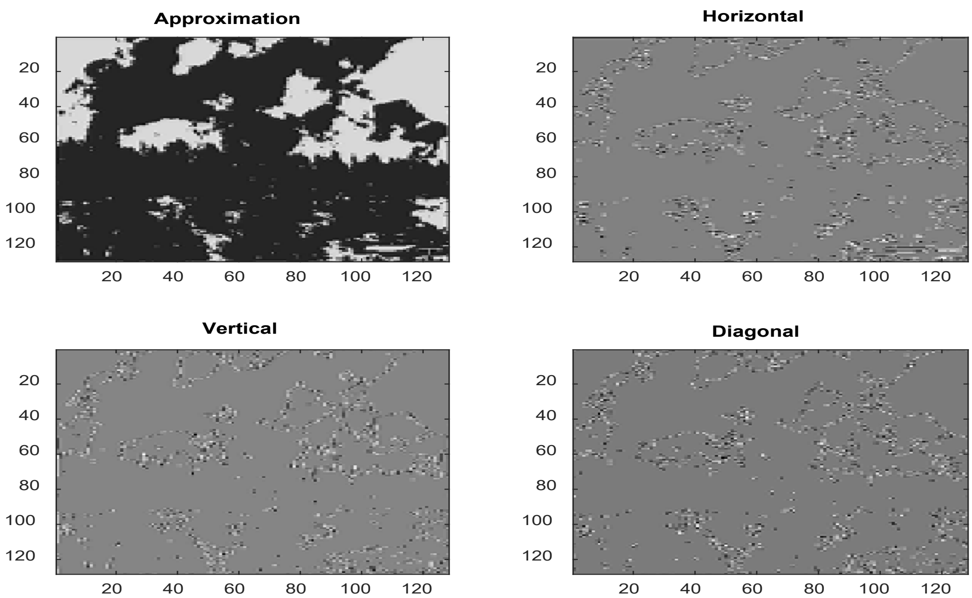
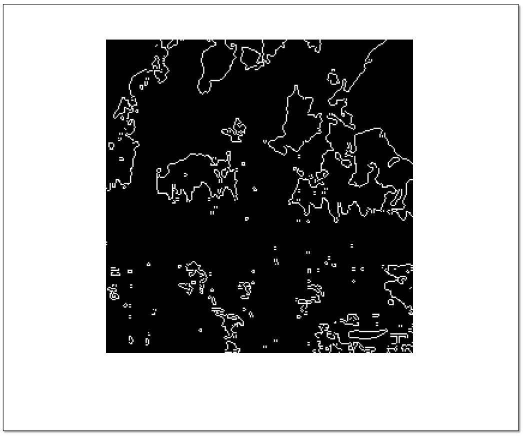
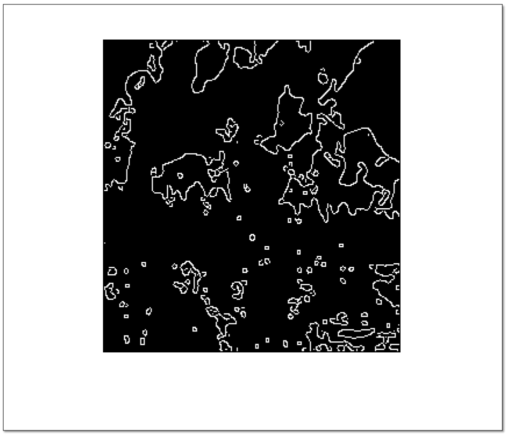


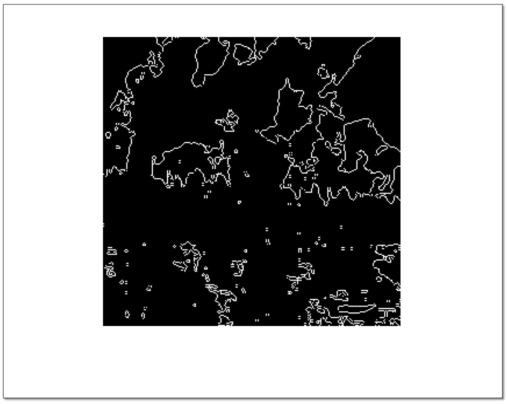
Figure 7. Approximation and Detail Coefficients (Horizontal, Vertical, and Diagonal) of FCM Segmentation Images



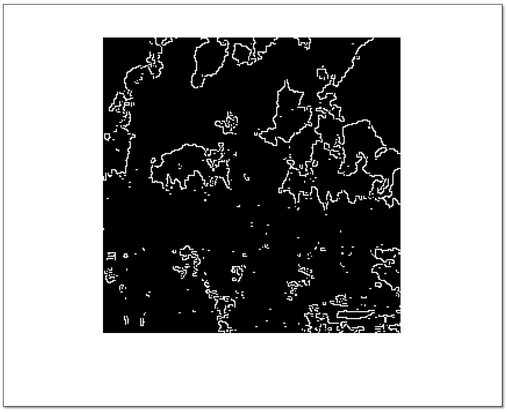
(a) Sobel-based Edge detected image



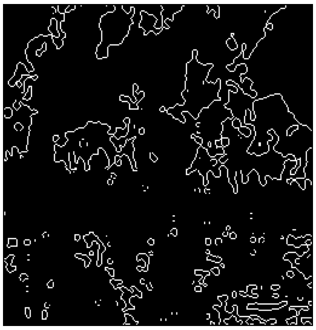
(b) Canny-based edge detected image



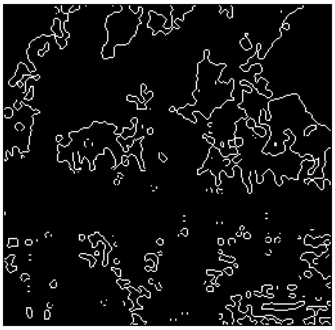
(c) Prewitt-based edge detected image



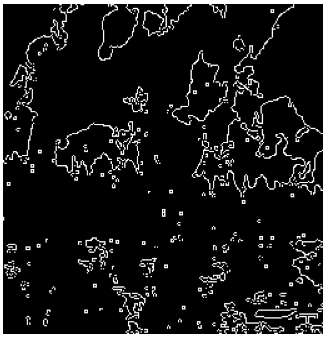
(d) Roberts-based edge detected image

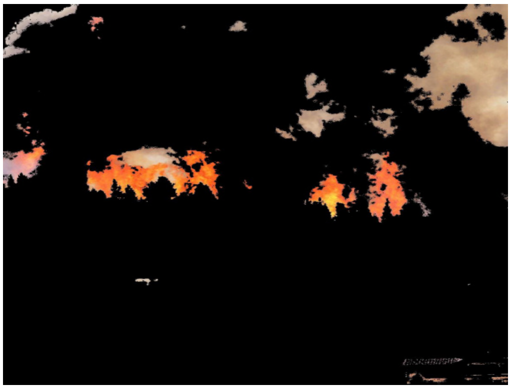


(e) Log-based edge detected image



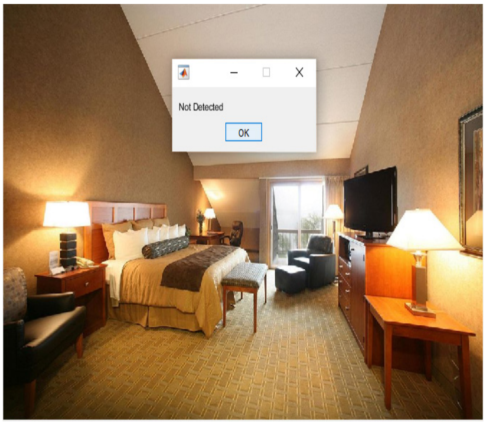
(f) Zero-cross-based edge detected image





(g) Approx-canny based edge detected image (g) Proposed fire detected image

Figure 8. Edge detection operators and proposed algorithm of fire detected image



(a) Fire detected image result (a) Non-fire detected image result

Figure 9. Fire detected and non-fire detected images

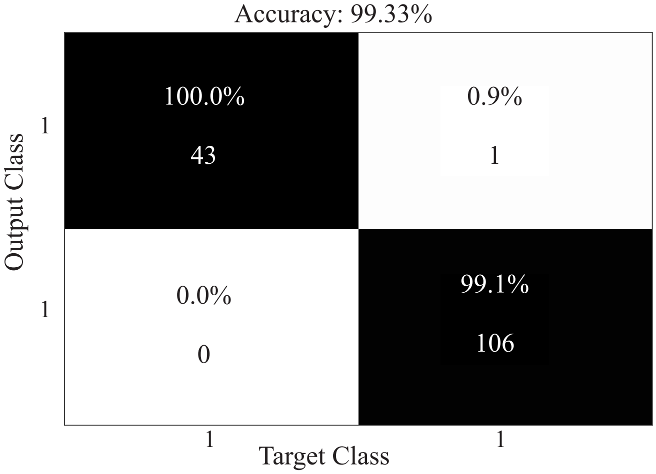


Figure 10. Confusion matrix of proposed optimum classifier

Table1

Performance parameters of proposed and existing methods

Performance Parameters/Methods	Muhammad et al. (2018)	Zhang et al. (2018)	Hou et al. (2019)	Huang et al. (2020)	Proposed Optimum Classifier
TP	100	101	102	104	**106**
TN	39	40	40	41	**43**
FP	6	5	4	3	**1**
FN	5	4	4	2	**0**
Accuracy(A)	92.67%	94.00%	94.67%	96.66	**99.33%**
Precision(P)	94.34%	95.28%	96.23%	97.19	**99.06%**
Sensitivity	95%	96%	96%	98.11	**100%**
Specificity	86.67%	88.89%	90.91%	93.18	**97.72%**
F1-Score	94.79%	95.73%	96.23%	97.65	**99.53%**
Training Accuracy					**70.67%**
Testing Accuracy					71.33%

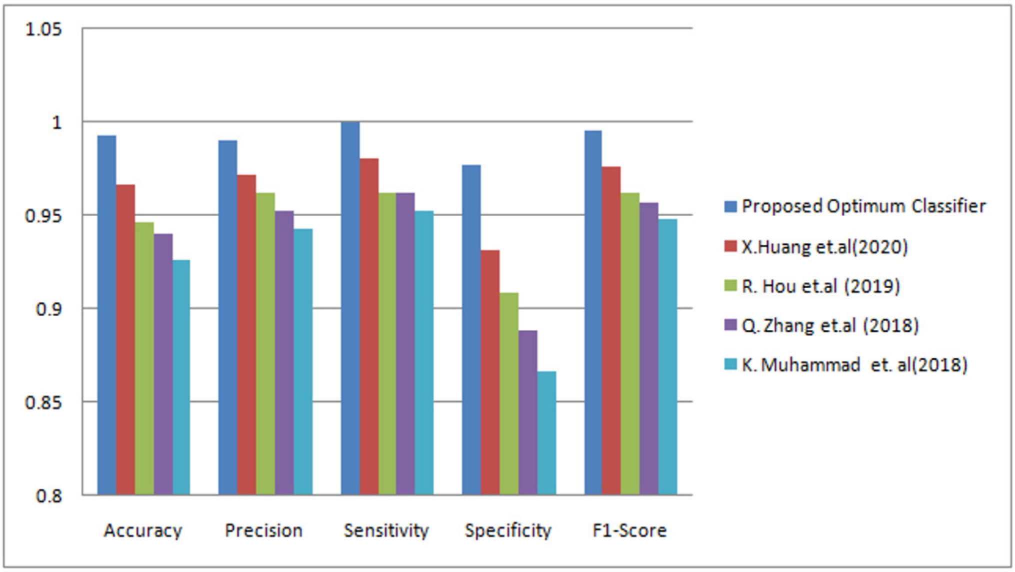


Figure 11. Comparison of Existing Methods Vs. Proposed Optimum Classifier

As shown in Figures 3 (a) and (b), original fired and non-fired images are used for testing the proposed method in the MATLAB simulation process (Sumathi & Paneerselvam, 2010).

Figure 4 shows the simulation results of pre-processed images of the originally fired image-1 for the preliminary process in this proposed work. First, the originally fired image-1 is resized into (256 x 256) pixels as shown in Figure 4 (a), grayscale and enhanced images results of test images as shown in Figure 4 (b) and (c), respectively.

Figure 5 (a) shows the binary version of the original enhanced fired image-1. The binary versions of the originally fired image-1 are segmented into two threshold levels using Fc-M clustering, and the results are shown in Figure 5 (b) and (c), respectively.

The overlay region of boundaries of Fc-M segmented image-1 is shown in Figure 6 (a). In Figure 6 (b), the red color represents the object boundaries, and the green color characterizes the hole boundaries of segmented fired image-1. The approximation and detailed coefficients (horizontal, vertical, and diagonal) are extracted from the Fc-M segmented test image-1, and the results are shown in Figure 7. The experimental fire detection images results of Sobel, Canny, Prewitt, Roberts, log, zero-cross, approx-canny edge detections and proposed fire detection as shown in Figure 8 (a), (b), (c), (d), (e), (f) and (g), respectively. The experimental results show that the proposed algorithm can detect fires effectively. The comparison results with seven classical edge detection operators show that the proposed algorithm performs superior to other edge detection operators. The MATLAB simulation proposed method results of fire-detected image-1 and non-fire-detected image-2 as shown in Figure 9 (a) and (b), respectively.

The performance values of the proposed method are evaluated using confusion matrix values, shown in Figure 10. In the proposed confusion matrix, TP is 106, TN is 43, FP is 1, and FN is 0. The performance parameters resulted from Muhammad et al. (2018), Zhang et al. (2018), Hou et al. (2019), and Huang et al. (2020), and proposed optimum classifiers are tabulated in Table 1. The proposed classifier accuracy value is 99.33%, precision value is 99.06%, sensitivity value is 100%, specificity value is 97.72%, F1-score value is 99.53%, training accuracy value is 70.67%, and testing accuracy value is 71.33 % (Table 1). Furthermore, the proposed method's performance values are higher than the other methods. The values of the proposed method and other methods from Table 1 are graphically depicted in Figure 11. The proposed graph optimum classifier shows significant improvement in all metric values compared to other methods.

CONCLUSION

In this study, the optimum SVM-based classifier of fire image recognition has been implemented for active fire detection. The classification is achieved effectively by using DWT and GLCM feature extraction. The results for fire detection were quantitatively and qualitatively evaluated. The experimental visual results show that the proposed fire recognition approach yields excellent robustness. This method's training and testing accuracies are 70.67% and 71.33%, respectively. The performance evaluation parameters of the proposed optimum classifier model significantly improved classification accuracy compared to other state-art algorithms. Future work will use satellite images with other feature extraction values for fast and higher-accuracy detection.

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REFERENCES

Ansari, M. D., & Ghrera, S. P. (2017). Copy-move image forgery detection using ring projection and modified fast discrete haar wavelet transform. *International Journal on Electrical Engineering and Informatics*, *9*(3), 542-552. https://doi.org/10.15676/ijeei.2017.9.3.9

Ansari, M. D., & Ghrera, S. P. (2018). Intuitionistic fuzzy local binary pattern for features extraction. *International Journal of Information and Communication Technology*, *13*(1), 83-98. https://doi.org/10.1504/IJICT.2018.090435

Ansari, M. D., Mishra, A. R., & Ansari, F. T. (2018). New divergence and entropy measures for intuitionistic fuzzy sets on edge detection. *International Journal of Fuzzy Systems*, *20*, 474-487. https://doi.org/10.1007/s40815-017-0348-4

Ansari, M. D., Mishra, A. R., Ansari, F. T., & Chawla, M. (2016). On edge detection based on new intuitionistic fuzzy divergence and entropy measures. In *2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC)* (pp. 689-693). IEEE Publishing. https://doi.org/10.1109/PDGC.2016.7913210

Chen, S., Du, H., Wu, L., Jin, J., & Qiu, B. (2017). Compressed sensing MRI via fast linearized preconditioned alternating direction method of multipliers. *Biomedical Engineering Online*, *16*, Article 53. https://doi.org/10.1186/s12938-017-0343-x

Cohen, A. (1994). Ten lectures on wavelets, CBMS-NSF regional conference series in applied mathematics. *Journal of Approximation Theory*, *78*(3), 460-461. https://doi.org/10.1006/jath.1994.1093

Coppo, P. (2015). Simulation of fire detection by infrared imagers from geostationary satellites. *Remote Sensing of Environment*, *162*, 84-98. https://doi.org/10.1016/j.rse.2015.02.016

Cristianini, N., & Shawe-Taylor, J. (2000). *An Introduction to Support Vector Machines and other Kernel-Based Learning Methods*. Cambridge University Press.

Dunnings, A. J., & Breckon, T. P. (2018). Experimentally defined convolutional neural network architecture variants for non-temporal real-time fire detection. In *2018 25th IEEE International Conference on Image Processing (ICIP)* (pp. 1558-1562). IEEE Publishing. https://doi.org/10.1109/ICIP.2018.8451657

Elaiyaraja, G., & Kumaratharan, N. (2015). Enhancing medical images by new fuzzy membership function median based noise detection and filtering technique. *Journal of Electrical Engineering and Technology*, *10*(5), 2197-2204. https://doi.org/10.5370/JEET.2015.10.5.2197

Elaiyaraja, G., Kumaratharan, N., & Rao, T. C. S. (2022). Fast and efficient filter using wavelet threshold for removal of Gaussian noise from MRI/CT scanned medical images/color video sequence. *IETE Journal of Research*, *68*(1),10-22. https://doi.org/10.1080/03772063.2019.1579679

Escalera, S., Pujol, O., & Radeva, P. (2009). Separability of ternary codes for sparse designs of error-correcting output codes. *Pattern Recognition Letters*, *30*(3), 285-297. https://doi.org/10.1016/j.patrec.2008.10.002

Esfahlani, S. S. (2019). Mixed reality and remote sensing application of unmanned aerial vehicle in fire and smoke detection. *Journal of Industrial Information Integration*, *15*(9), 42-49. https://doi.org/10.1016/j.jii.2019.04.006

Fan, R. E., Chen, P. H., Lin, C. J., & Joachims, T. (2005). Working set selection using second order information for training support vector machines. *Journal of Machine Learning Research*, *6*(12), 1889-1918.

Filizzola, C., Corrado, R., Marchese, F., Mazzeo, G., Paciello, R., Pergola, N., & Tramutoli, V. (2016). RST-FIRES, an exportable algorithm for early-fire detection and monitoring: Description, implementation, and field validation in the case of the MSG-SEVIRI sensor. *Remote Sensing of Environment*, *186*, 196-216. https://doi.org/10.1016/j.rse.2016.08.008

Fürnkranz, J. (2002). Round robin classification. *The Journal of Machine Learning Research*, *2*, 721-747.

Garcia-Jimenez, S., Jurio, A., Pagola, M., De Miguel, L., Barrenechea, E., & Bustince, H. (2017). Forest fire detection: A fuzzy system approach based on overlap indices. *Applied Soft Computing*, *52*, 834-842. https://doi.org/10.1016/j.asoc.2016.09.041

Genovese, A., Labati, R. D., Piuri, V., & Scotti, F. (2011). Virtual environment for synthetic smoke clouds generation. In *2011 IEEE International Conference on Virtual Environments, Human-Computer Interfaces and Measurement Systems Proceedings* (pp. 1-6). IEEE Publishing. https://doi.org/10.1109/VECIMS.2011.6053841

Gottuk, D. T., Lynch, J. A., Rose-Pehrsson, S. L., Owrutsky, J. C., & Williams, F. W. (2006). Video image fire detection for shipboard use. *Fire Safety Journal*, *41*(4), 321-326. https://doi.org/10.1016/j.firesaf.2005.12.007

Hackner, A., Oberpriller, H., Ohnesorge, A., Hechtenberg, V., & Müller, G. (2016). Heterogeneous sensor arrays: Merging cameras and gas sensors into innovative fire detection systems. *Sensors and Actuators B: Chemical*, *231*(8), 497-505. https://doi.org/10.1016/j.snb.2016.02.081

Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer.

Hou, R., Pan, M., Zhao, Y., & Yang, Y. (2019). Image anomaly detection for IoT equipment based on deep learning. *Journal of Visual Communication and Image Representation*, *64*(10), 212-223. https://doi.org/10.1016/j.jvcir.2019.102599

Huang, X., & Du, L. (2020). Fire detection and recognition optimization based on virtual reality video image. *IEEE Access*, *8*, 77951-77961. https://doi.org/10.1109/ACCESS.2020.2990224

Jia, Y., Yuan, J., Wang, J., Fang, J., Zhang, Q., & Zhang, Y. (2016). A saliency-based method for early smoke detection in video sequences. *Fire Technology*, *52*, 1271-1292. https://doi.org/10.1007/s10694-014-0453-y

Kapil, S., Chawla, M., & Ansari, M. D. (2016). On K-means data clustering algorithm with genetic algorithm. In *2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC)* (pp. 202-206). IEEE Publishing. https://doi.org/10.1109/PDGC.2016.7913145

Kecman, V., Huang, T. M., & Vogt, M. (2005). Iterative single data algorithm for training kernel machines from huge data sets: Theory and performance. In L. Wang (Ed). *Support Vector Machines: Theory and Applications* (pp. 255-274). Springer. https://doi.org/10.1007/10984697_12

Koltunov, A., Ustin, S. L., Quayle, B., Schwind, B., Ambrosia, V. G., & Li, W. (2016). The development and first validation of the GOES early fire detection (GOES-EFD) algorithm. *Remote Sensing of Environment*, *184*, 436-453. https://doi.org/10.1016/j.rse.2016.07.021

Li, P., & Zhao, W. (2020). Image fire detection algorithms based on convolutional neural networks. *Case Studies in Thermal Engineering*, *19,* Article 100625. https://doi.org/10.1016/j.csite.2020.100625

Li, T. S. (2009). Applying wavelets transform and support vector machine for copper clad laminate defects classification. *Computers and Industrial Engineering*, *56*(3), 1154-1168. https://doi.org/10.1016/j.cie.2008.09.018

Lin, Z., Chen, F., Niu, Z., Li, B., Yu, B., Jia, H., & Zhang, M. (2018). An active fire detection algorithm based on multi-temporal FengYun-3C VIRR data. *Remote Sensing of Environment*, *211*, 376-387. https://doi.org/10.1016/j.rse.2018.04.027

López-García, D., Peñalver, J. M., Górriz, J. M., & Ruz, M. (2022). MVPAlab: A machine learning decoding toolbox for multidimensional electroencephalography data. *Computer Methods and Programs in Biomedicine*, *214*, Article 106549. https://doi.org/10.1016/j.cmpb.2021.106549

Mallat, S.G (1989). A theory for multi-resolution signal decomposition: The wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *11*(7), 674-93. https://doi.org/10.1109/34.192463

Meyer, Y. (1995). *Wavelets and Operators*. Cambridge University Press.

Muhammad, K., Ahmad, J., & Baik, S. W. (2018). Early fire detection using convolutional neural networks during surveillance for effective disaster management. *Neurocomputing*, *288*, 30-42. https://doi.org/10.1016/j.neucom.2017.04.083

Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, *9*(1), 62-66.

Peng, Y., & Wang, Y. (2019). Real-time forest smoke detection using hand-designed features and deep learning. *Computers and Electronics in Agriculture*, *167*, Article 105029. https://doi.org/10.1016/j.compag.2019.105029

Scholkopf, B., & Smola, A. J. (2018). *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*. MIT Press.

Schölkopf, B., Platt, J. C., Shawe-Taylor, J., Smola, A. J., & Williamson, R. C. (2001). Estimating the support of a high-dimensional distribution. *Neural Computation*, *13*(7), 1443-1471. https://doi.org/10.1162/089976601750264965

Seydi, S. T., Saeidi, V., Kalantar, B., Ueda, N., & Halin, A. A. (2022). Fire-Net: A deep learning framework for active forest fire detection. *Journal of Sensors*, *2022*, Article 8044390.

Sharma, A., Ansari, M. D., & Kumar, R. (2017). A comparative study of edge detectors in digital image processing. In *2017 4th International Conference on Signal Processing, Computing and Control (ISPCC)* (pp. 246-250). IEEE Publishing. https://doi.org/10.1109/ISPCC.2017.8269683

Singh, C., Walia, E., & Kaur, K. P. (2018). Enhancing color image retrieval performance with feature fusion and non-linear support vector machine classifier. *Optik*, *158*(3), 127-141. https://doi.org/10.1016/j.ijleo.2017.11.202

Sumathi, S., & Paneerselvam, S. (2010). *Computational Intelligence Paradigms: Theory & Applications using MATLAB*. CRC Press. https://doi.org/10.1201/9781439809037

Xiong, G. (2021). *Fuzzy c-means thresholding*. MATLAB central file exchange. https://www.mathworks.com/matlabcentral/fileexchange/8351-fuzzy-c-means-thresholding

Zeng, Y., Zhou, Z., Chen, J., & Liu, W. (2006). An Improved UWB transmitted reference system based on wavelet decomposition. In *IEEE Vehicular Technology Conference* (pp. 1-5). IEEE Publishing. https://doi.org/10.1109/VTCF.2006.203

Zhang, Q. X., Lin, G. H., Zhang, Y. M., Xu, G., & Wang, J. J. (2018). Wildland forest fire smoke detection based on faster R-CNN using synthetic smoke images. *Procedia Engineering*, *211*(1), 441-446. https://doi.org/10.1016/j.proeng.2017.12.034