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MULTIVARIATE REGRESSIVE FULLY RECURRENT NEURAL CLASSIFIER FOR FIRE DETECTION

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ABSTRACT

Background: *Forest fire is a demanding function to identify fire from visual scenes or videos due to substantial dissimilarities in the feature of color, texture, intensity, shapes, and so on. The current fire detection mechanisms are specifically designed by considering all features, but increasing the complexity, which results in low fire detection accuracy or higher error rate.* ***Methods:*** *To attain higher fire detection accuracy and reduce the error rate, a Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) method is presented for forest fire detection using a time series model. Firstly, a Histogram Mean Frame Extraction algorithm based on histogram and mean function is proposed to extract the inherent frame. Then, the fire features are extracted by using the Multivariate Robust Statistical Feature Extraction algorithm. Finally, the classification between features is made using the Multivariate Robust Regressive model, and accordingly, the detection of fire is made accurately with less error rate by applying the Fully Recurrent Neural Classifier.* ***Results:*** *The results illustrate that the MR-FRNC method increases fire detection accuracy by 19% and reduces the false positive rate by 68% as compared to state-of-the-art works.* ***Conclusions:*** *Our algorithm improves fire detection accuracy with minimum complexity. Also, the algorithm has good fire detection performance by testing under various video scenes.*

KEY WORDS
Histogram, Mean Frame Extraction, Multivariate, Regressive, Fully Recurrent Neural Classifier

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INTRODUCTION

Forest fire is one of the most important natural agents that change the terrestrial ecosystems in the earth. Fusing raster classification with pixel-based time series was presented in [1] for analyzing the changes observed in the forest using Landsat data at the large-area scale. However, the time consumed in generating the decision tree for random forest generation was found to be higher. A novel radar-based burned area mapping algorithm was designed in [2] based on change detection guided by thermal anomalies. However, the misclassification of the burned area was not reduced and hence the accuracy was found to be compromised.

The remainder of the paper is organized as follows: Related work is presented in detail Section 2. Section III describes the detection of fire regions and describes the proposed MR-FRNC method with a neat diagram and algorithms. Finally, experimental results are discussed in Section 4, while conclusions are drawn in Section 5.

A novel land cover model was developed in [3] using Monte Carlo estimation of nonlinear time-varying parameters for early fire detection. However, accuracy detection was not said to be performed with minimum time complexity. Yet another method using linear regression analysis was designed in [4] using the Burned Area Spectral Mixture Analysis (BASMA) algorithm. A Random Forest classifier was introduced in [5] to calculate class probabilities for all pixels in the time series for detecting the fire. A Continuous Subpixel Monitoring (CSM) technique was introduced in [6] by constructing the random forest regression models. Logistic regression and temporal smoothing were introduced in [7] for fire flame detection in surveillance video. In [8], a computer vision approach for fire-flame detection was used by an early-warning fire monitoring system. A case study of fire reports involving the extraction steps required was detailed in [9]. A cost-effective fire detection method using a convolutional neural network (CNN) for surveillance videos was presented in [10]. Yet another dynamic channel selection algorithm was designed in [11] for CCTV surveillance cameras. In [12], a smoke detection algorithm was designed based on the motion characteristics of smoke and the convolutional neural networks (CNN). Transfer learning using deep neural networks was applied in [13] for detecting side fire data. In [14], a spatial prediction model was designed and hyper parameters were optimized to improve the prediction accuracy. In [15], learning in recurrent neural networks was performed using tangent planes. However, the false positive rate was not considered. To address this issue, in [16], both local and global analyses were carried out for image-based early warning system. Fire detection in the aspect of the dynamical system was presented in [17] using mutual information and multidimensional scaling. A detailed comparison of the fire mapping system called a hazard mapping system was designed in [18] to increase the detection rate. However, with the lack of localization, accuracy with complexity was not addressed. To focus upon on this issue, in [19], a computationally efficient CNN architecture was presented. Rule-based image processing algorithm was designed in [20] for forest fire detection. A real-time dynamic texture recognition method was introduced in [21] for texture recognition of flame with a minimum computational cost. A vision-based method to detect smoke using Deep Convolution Generative Adversarial Neural Networks (DC-GANs) was implemented in [22]. Multiplication-free neural network (AddNet) architecture was designed for forest fire detection in [23]. Aim of the work: To increase the fire detection accuracy with minimum time complexity, Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) is introduced. To reduce the computational complexity involved in fire detection, Histogram Mean Frame Extraction model is used. To reduce the processing time, Multivariate Robust Statistical Feature Extraction (MRS-FE) model is applied. To minimize

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the least absolute error of the forest fire detection, the Multivariate Robust Regressive model employed in the deep learning via polynomial regression. To reduce the complexity and the error, Fully Recurrent Neural Learning Classifier (FRNLC) model is applied.

METHODS

In this section, a Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) for forest fire detection using a time series model with higher accuracy and lesser time complexity is presented. [Fig. 1] shows the flow diagram of the MR-FRNC method.

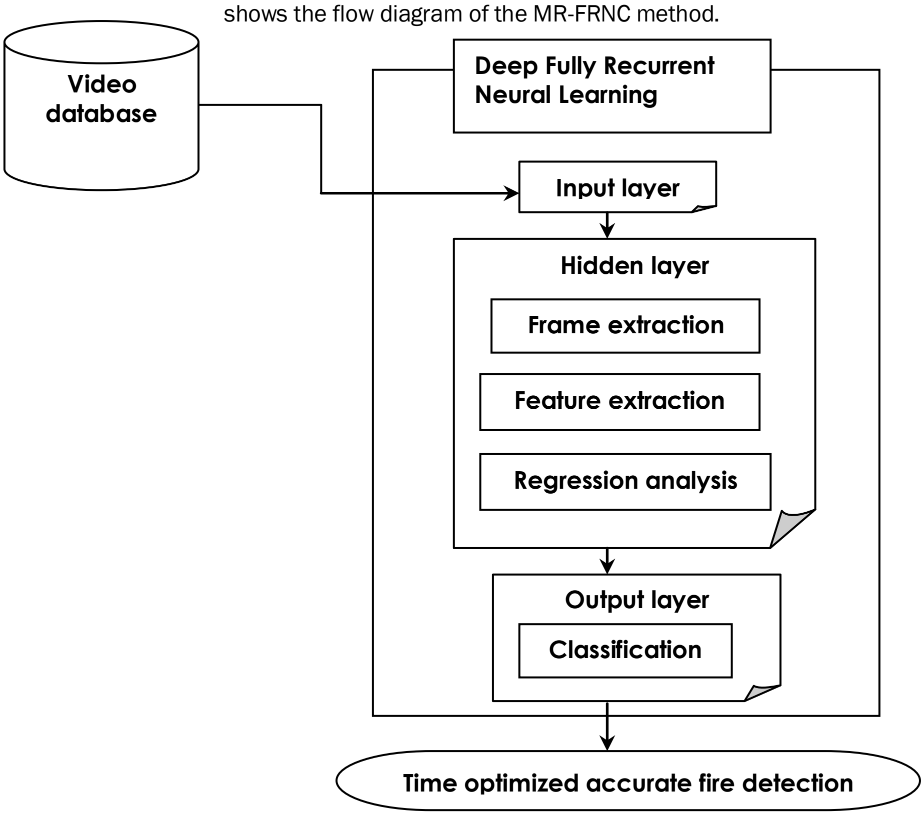

Fig. 1: Flow diagram of MR-FRNC method

As shown in the figure, the Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) method uses three different layers, such as the input layer, three hidden layers, and the output layer for forest fire detection. In the input layer, the video database, FIRESENSE database of videos for flame and smoke detection [21] is used as input. In the input layer, the video sequences are provided as input. Next, forms the three hidden layers, the first hidden layer for frame extraction, the second hidden layer for feature extraction, and the third hidden layer for estimating the relationships between variables (i.e. features). Finally, in the output layer, classification is performed for forest fire detection.

Frame extraction - histogram mean frame extraction model

With the input FIRESENSE database provided as input to acquire the videos for flame and smoke detection, the first step forms the frame extraction. In this work frame extraction from the input, a video database is performed by applying the histogram mean function. The pseudo-code representation of Histogram Mean Frame Extraction is given below.

Input: Video database '$V = V_1, V_2, \dots, V_n$', Frame '$F = F_1, F_2, \dots, F_m$'
Output: Inherent frame extraction 'InF'
1: Begin 2: For each video database '$V = V_1, V_2, \dots, V_n$' with Frame 'F' 3: Obtain matrix representation using (2) 4: Obtain candidate keyframes using (3) 5: Obtain optimized keyframes using (6) 6: End for 7: Return (inherent frames '$InF = InF_1, InF_2, \dots, InF_m$') 8: End

Algorithm 1 Histogram Mean Frame Extraction

As given in the above algorithm, let us assume that the video database consists of 'n' number of sample video files '$V = V_1, V_2, \dots, V_n$' and each video consists 'm' number of frames is represented as given below.

$$V = V_i = F_1, F_2, \dots, F_m \quad (1)$$

With the overall frames '$F_1, F_2, \dots, F_m$' for each video 'V_i', the frames are first obtained by storing the frames of the subsequent videos in matrix representation. This is expressed as given below.

$$V = \begin{bmatrix} V_1F_1 & V_1F_2 & \dots & V_1F_m \\ V_2F_1 & V_2F_2 & \dots & V_2F_m \\ \dots & \dots & \dots & \dots \\ V_nF_1 & V_nF_2 & \dots & V_nF_m \end{bmatrix} \quad (2)$$

Followed by the matrix representation, the candidate key frames are obtained via the histogram of all frames. This is expressed as given below.

$$CKF = \frac{HIS[V_iF_i]}{n} \quad (3)$$

From the above equation (3), the candidate keyframes 'CKF' are extracted by applying the histogram value of the pixel in a specific location of the video. To obtain the histogram value, first the overall frames 'm' is observed. Then, the sample frame ranges are said to be obtained by measuring the difference between the highest value '$HV[V_iF_i]$' (i.e. highest frame pixel) and the lowest value '$LV[V_iF_i]$' (i.e. lowest frame pixel). This is mathematically expressed as given below.

$$HIS[V_iF_i] = HV[V_iF_i] - LV[V_iF_i] \quad (4)$$

With the obtained candidate keyframes, finally, the optimized keyframes are obtained via a mean function. This is mathematically expressed as given below.

$$\sigma_{pq} = \sum_{i=1}^{N}(p_i - \mu_i)(q_i - \mu_i) \quad (5)$$

In the histogram mean model, the mean histogram of all the frames is evaluated. Next, all the frames whose histogram is nearer to the mean histogram are chosen as the keyframe. This is mathematically expressed as given below.

$$InF = SIM(p,q) = CKF \left[\frac{\sigma_{pq}}{\sigma_p \sigma_q}\right] * HIS[V_iF_i] \quad (6)$$

The extracted frames now form the input to the second hidden layer. This frame possesses the advantage of both low computational complexity and also possessing mean representative meaning.

Multivariate robust statistical feature extraction model

In this work, to reduce the processing time involved in detecting fires, Multivariate Robust Statistical Feature Extraction (MRS-FE) model is used using two different descriptors, forming vital factors. Those visual factors are either in the form of low-level descriptors like color, shape, texture, or high-level descriptors like spatiotemporal energy color, motion, and temperature or intensity. With the two said descriptors, optimized fire features are said to be extracted. The pseudo-code representation of Multivariate Robust Statistical Feature Extraction is given below.

Input: Inherent frame extraction 'InF'
Output: Optimized fire features 'OpF'
1: Begin 2: For each inherent frame extracted 'InF' 3: Measure color analysis using equation (7) and (8) 4: Measure fire shape analysis using equation (9) and (10) 5: Obtain texture analysis using equation (11) 6: Obtain Spatio Temporal Energy Color using equation (12) 7: Obtain motion and temperature analysis using equation (15), (16), and (17) 8: Obtain intensity analysis using equation (18) 9: Return (Optimized fire features 'OpF') 10: End for 11: End

Algorithm 2 Multivariate Robust Statistical Feature Extraction

As given in the above algorithm, fire color analysis involves the calculations that are used in our work to discriminate fire images. In our work, two pivotal instant of fire (inherent feature) image color distribution like mean and standard deviation are utilized. Besides, RGB (Red, Green, and Blue) color is used to define

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three instants for each three color channels. Then, the mean and standard deviation of the 'ith' color channel at the 'jth' inherent frame is obtained and expressed as given below.

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} InF_{ij} \quad (7)$$

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(InF_{ij} - \mu_i\right)^2} \quad (8)$$

From the above two equations (7) and (8), fire color analysis of the inherent frame extracted 'InF' for several videos are obtained. Next, the fire shape normally varies approximately and swiftly in comparison to the comparatively smooth features of other objects in the inherent frame extracted. In this work, objects actual perimeter length 'PL' and perimeter length proportion 'PLP' of the convex body nearest to this object is used to ascertain the exterior of the fire. They are expressed as given below.

$$PL = InF_i * 4S \quad (9)$$

$$PLP = \frac{1}{N}\sum_{i=1}^{N} PL_i \quad (10)$$

Next, the third texture analysis is arrived at based on the weighted divergence analysis and is mathematically formulated as given below.

$$D(L) = \frac{\sum_{i=1}^{N} W(InF_i - \mu)^2}{N} \quad (11)$$

From the above equation (11), the divergence analysis 'D' for label 'L' refers to the specific connecting feature (i.e. inherent frame) with 'µ' and 'N' representing the mean value and the overall frames considered for testing. 'W' denotes the Weight function. With the above three local descriptors, values are logically and with the three global descriptors. To start with the first global descriptor, Spatio Temporal Gabor wavelet measured. This is obtained using triplet frequency elements in horizontal 'H', vertical 'V', and diagonal 'D' directions. The Spatio Temporal Energy Color of the video in inherent frame 'InF_i' is defined as given below.

$$STEn_i(\theta, T) = \frac{\sum(p,q) \in InF_i \, wc(p,q)}{\sum(p,q) \in InF_i \, WC(p,q)} \quad (12)$$

$$wc\,(p,q) = H(p,q) + L(p,qv) + D(p,q) \quad (13)$$

$$WC(p,q) = D(p,q) \quad (14)$$

From the above equation (12), the spatiotemporal energy color analysis '$STEn_i$' is obtained based on the wavelet coefficient of the horizontal, vertical and diagonal directions '$wc\ (p,q)$' and the overall wavelet coefficients that refer to the diagonal parts '$WC(p,q)$' respectively. Besides 'θ' and 'T' represents the direction and magnitude. Next, the motion and temperature analysis and intensity analysis work in coordination with each other. To obtain the motion temperature and intensity analysis, the average of the three components, Red, Green, and Blue space in the entire video is obtained as follows.

$$R_{mean} = \frac{1}{N}\sum_{i=1}^{N} R(p_i, q_i) \quad (15)$$

$$G_{mean} = \frac{1}{N}\sum_{i=1}^{N} G(p_i, q_i) \quad (16)$$

$$B_{mean} = \frac{1}{N}\sum_{i=1}^{N} B(p_i, q_i) \quad (17)$$

For certain high temperature, vicinity to white color, detection of high-intensity fire are not said to be possible. Hence, the color model is split into three channels and their mean values are obtained from (15), (16), and (17). Based on the results, intensity fire analysis is made. They are normal intensity fire and high-intensity fire. This is mathematically obtained as given below.

$$I(p,q) = \begin{cases} 1, if\ InF(p,q) > R_{mean} \cup G_{mean} \cup B_{mean} \\ \quad 0, Otherwise \end{cases} \quad (18)$$

Finally, from the above local and global descriptors, the features extracted that characterize the fire features are obtained as given below.

$$FE = \mu_i \cup \sigma_i \cup PLR \cup D(L) \cup STEn_i(\theta, T) \cup R_{mean} \cup G_{mean} \cup B_{mean} \cup I(p,q) \tag{19}$$

Finally, all the salient features extracted are combined to produce the final features being extracted. As only the salient and optimized features are extracted and used for further analysis, the processing time involved in fire detection is said to be reduced.

Multivariate robust regressive model

In the third hidden layer, a polynomial regression analysis is carried out to detect the fire in the given video frame with multiple extracted features hence the name is called a Multivariate Robust Regressive model. The Multivariate Robust Regressive model used in deep learning via polynomial regression reduces the least absolute error of the forest fire detection. The Polynomial Regression procedure for fire detection is intended to design a statistical model depicting the influence of a single quantitative factor X (i.e. inherent frames extracted) on a dependent variable Y (i.e. features extracted). A polynomial model involving inherent frames extracted and powers of features extracted is fit to the data. This is expressed as given below.

$$c_0 + c_1 p + c_2 p^2 + c_3 p^3 + \dots c_n p^n = RInF \tag{20}$$

$$RInF = \begin{bmatrix} 1 & p_1 & p_1^2 & \dots \\ 1 & p_2 & p_2^2 & \dots \\ 1 & p_3 & p_3^2 & \dots \\ \dots & \dots & \dots & \dots \\ 1 & p_n & p_n^2 & \dots \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ \dots \\ c_n \end{bmatrix} \approx \begin{bmatrix} q_1 \\ q_2 \\ q_3 \\ \dots \\ q_n \end{bmatrix} \tag{21}$$

From the above equation (20) and (21), 'p' and 'q' corresponds to coefficients denoted by 'c_0', 'c_1'... 'c_n'. Here, the coefficients 'c_0' refers to the optimal features extracted.

Fully recurrent neural learning classifier for forest fire detection

Finally, the output is obtained at the output layer with minimum error using the Fully Recurrent Neural Learning Classifier. To reduce the complexity and also to minimize the error, in this work, the Fully Recurrent Neural Learning Classifier (FRNLC) model is used. This helps to improve fire detection accuracy and minimize the false positive rate. The pseudo-code representation of Fully Recurrent Neural Learning Classifier is given below.

```
Input: Optimized fire features 'OpF'
Output: Accurate fire detection
Initialize regressive features 'RInF'
Begin
    For each Optimized fire features 'OpF'
        Formulate recurrent neural network using equation (22)
        Formulate classification result using equation (23)
        If 'Prob_0' then
            Possibility of fire
        End if
        If 'Prob_1' then
            No possibility of fire
        End if
    End for
End
```

Algorithm 3 Fully Recurrent Neural Learning Classifier

From the above algorithm, initially, optimized fire features are provided as input. Next, the regressive features are initialized for the classification of fire images and perform fire detection. Due to the nonlinearity nature of data (i.e. fire), in this work, Fully Recurrent Neural Learning Classifier is applied to the fire features extracted for fire detection. The main advantage of using this type of FRNLC classifier is the existence of a feedback mechanism in the nodes of the recurrent network. The FRNLC is formulated as given below

$$h(T) = \left| Fun_H \left(W_I(p(T)) \right) + W_H(h(T-1)) \right| \tag{22}$$

$$q(T) = \left[Fun_O(W_O h(T)) \right] \tag{23}$$

From the above equations (22) and (23), let us consider the neural network inputs and outputs as the vectors '$p(T)$' and '$q(T)$', with the three connection weight matrices being 'W_I', 'W_H' and 'W_O', and the hidden and output unit activation functions being 'Fun_H' and 'Fun_O', the behavior of the recurrent network is then described by the pair of non-linear matrix equations. The network uses the output function 'q(T)' to realize feature classification after the last non-linear matrix equations. The output function 'q(T)' is then utilized to measure the probability that the eigenvectors belong to each class. The probability vector '<⟦Prob⟧_0,⟦Prob⟧_1' is then said to be obtained in our algorithm, with '⟦Prob⟧_0' representing the probability that the suspected region belongs to the fire region and '⟦Prob⟧_1' represents the probability that the suspected region does not belong to the fire region. The final classification results are obtained through the equation (23) and on that, the detection of fire is said to be performed ultimately.

RESULTS

In this section, the result of the MR-FRNC method is compared with existing methods namely, fusing raster classification with pixel-based time series [1], and novel radar based burned area mapping algorithm [2] is implemented in MATLAB using the FIRESENSE database [21]. The result is carried out on factors such as fire detection accuracy, computational complexity, time complexity, and false positive rate with respect to a number of video frames.

Qualitative analysis

In this section, the qualitative analysis of fire detection is presented. With the input video obtained from FIRESENSE are input, first, inherent frames are extracted. With the extracted inherent frames, certain features for further classification are acquired in the output layer, here training images (i.e., input image) are compared with a testing image (Pre-stored), and their qualitative is analyzed.

Performance measure of fire detection accuracy

One of the most important metrics in analyzing fire detection is the accuracy rate. The fire detection accuracy in this work is referred to as the percentage ratio of the number of video frames properly detected with fire $Fire_{Det}$ to the number of video frames F_i provided as input.

$$FDA = \sum_{i=1}^{N} \frac{Fire_{Det}}{F_i} * 100 \quad (\%) \qquad (24)$$

From the above equation (24), the accuracy rate 'FDA' is measured according to the fire detected rate to the sample's video frames and is measured in terms of percentage (%). A higher accuracy rate ensures the efficiency of the method.

Table 1: Results of the fire detection accuracy

Number of video frames	Fire detection accuracy (%)		
	Proposed MR-FRNC method	Fusing raster classification with pixel-based time series	Novel radar based burned area mapping algorithm
25	98	84	80
50	96	82	78
75	95	80	75
100	92	78	74
125	95	80	75
150	94	81	77
175	93	82	75
200	91	80	74
225	89	82	72
250	87	80	74

The results of the fire detection accuracy are shown in [Table 1]. The result of the fire detection accuracy is increased by 15% as compared to fusing raster classification with pixel-based time series [1] and 23% as compared to novel radar based burned area mapping algorithm [2].

Performance measure of fire detection computational complexity

The second parameter used for fire detection is the computational complexity rate. The computational complexity is measured as given below.

$$FDCC = \sum_{i=1}^{N} F_i * MEM\,[Fire_{Det}] \qquad (25)$$

From the above equation (25), the fire detection computational complexity $FDCC$ is measured based on the number of video frames 'F_i' and the memory consumed in fire detection $MEM\,[Fire_{Det}]$. It is measured in terms of kilobytes (KB). Lower complexity measures the efficiency of the method.

Table 2: Results of the computational complexity

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Number of video frames	Computational complexity (KB)		
	MR-FRNC	Fusing raster classification with pixel-based time series	Novel radar based burned area mapping algorithm
25	50	75	100
50	100	150	175
75	125	175	225
100	125	200	250
125	150	225	255
150	175	250	275
175	200	275	300
200	250	275	325
225	275	300	350
250	300	325	375

The results of the computational complexity are shown in [Table 2]. The result of the computational complexity is reduced by 25% as compared to fusing raster classification with pixel-based time series [1] and 36% as compared to novel radar based burned area mapping algorithm [2].

Performance measure of time complexity

The third parameter used in measuring fire detection is the time complexity involved. Lower the time complexity involved in fire detection, swift is the action to be taken place, and therefore the method is said to be efficient. It is measured as milliseconds (ms) and given below.

$$TC = \sum_{i=1}^{N} F_i * Time\ [Fire_{Det}] \quad (26)$$

From the above equation (26), the time complexity 'TC', is measured according to the video frames considered 'F_i' and the time involved in fire detection '$Time\ [Fire_{Det}]$'.

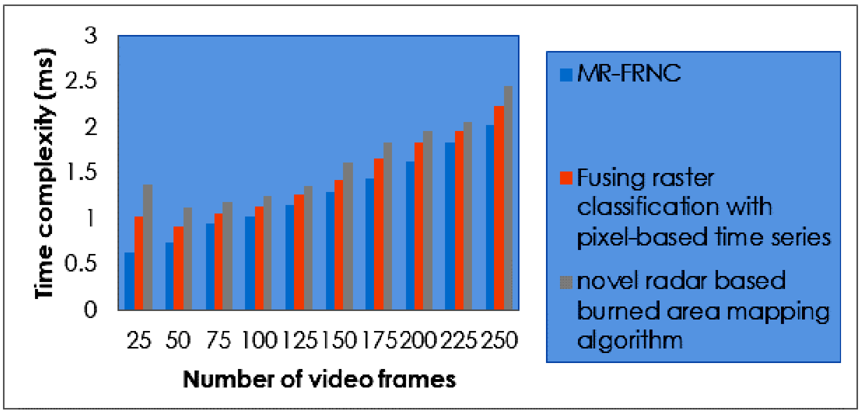

Fig. 2: Result of time complexity

The result of time complexity is presented in [Fig. 2]. The result of time complexity involved using MR-FRNC method was found to be reduced by 14% as compared to fusing raster classification with pixel-based time series [1] and 23% as compared to novel radar based burned area mapping algorithm [2].

Performance measure of false positive rate

Finally, the parameter used in measuring fire detection is the error involved. It is defined as the ratio of the number of frames that are incorrectly classified to the total number of video frames as input. The FPR is determined in terms of percentage (%) and mathematically estimated as,

$$FPR = \frac{M_{ic}}{n} * 100 \quad (27)$$

Here, 'M_IC' represents the number of frames that are inaccurately classified and 'm' refers a total number of video frames.

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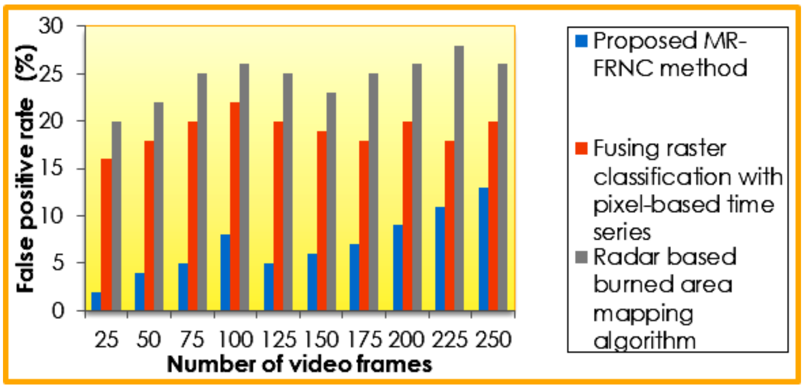

Fig. 3: Result of false positive rate

The result of false positive rate is presented in [Fig. 3].As a result, the false positive rate involved using MR-FRNC method was found to be reduced by 63% compared to fusing raster classification with pixel-based time series [1] and 72% compared to novel radar based burned area mapping algorithm [2].

DISCUSSION

In this section, the proposed MR-FRNC method is used to improve the forest fire detection performance in terms of fire detection accuracy, computational complexity, time complexity, and false positive rate. The fire detection accuracy with respect to 250 different video frames obtained from different videos at different time intervals in [Table 1]. With the '25' number of video frames provided as input, the existing fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2] obtains '84' and 80' frames of detection accuracy. Whereas '90 frames is achieved in MR-FRNC method. From that fire detection accuracy is better than existing methods. By applying Fully Recurrent Neural Learning Classifier algorithm, a feedback mechanism is included that uses the information (i.e. features) from the preceding samples along with the present inputs. This is in turn increases the fire detection accuracy by using MR-FRNC method. In [Table 2] shows the computational complexity for 250 different video frames acquired from different videos at different time intervals. With the '25' number of video frames provided as input, the existing fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2] obtains '75KB' and 100KB' frames of computational complexity. Whereas 50KB frames complexity is achieved in MR-FRNC method. The computational complexity was found to be better than fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2]. By applying Histogram Mean Frame Extraction algorithm, inherent frames are first extracted from the given input videos. Here, three different steps are applied, first a matrix representation of video to the corresponding frames are formed, followed by which, candidate key frames are applied using the statistical model and finally, a histogram model is applied to obtain optimized key frames. Though three steps are applied in extracting the inherent frames, it is computationally efficient. Hence, the computational complexity was found to be less by using MR-FRNC method.

The novelty involved in the technique can be described as:

We propose a Fully Recurrent Neural Learning Classifier along with the Multivariate Robust Regressive model that not only improves the accuracy but also reduces the error. A novel method is proposed for fire detection based on the combination of local and global descriptors extracted from spatiotemporal fire modeling and inherent frame extraction analysis. In this way, the proposed method not only concentrates on the detection of local descriptors (e.g. analysis of color, texture, shape) but also exploits also the global descriptors (e.g. analysis of spatiotemporal energy, motion temperature, and intensity) to analyze both the spatial and temporal ability of fire detection systems to increase the robustness of the algorithm. An efficient fire detection modeling is introduced to identify the color of the fire, texture of the fire, and the texture characteristics as well as the intensity and temperature analysis. A novel model for enhancing the fire detection accuracy by applying the Fully Recurrent Neural Learning Classification algorithm is introduced by exploiting: i) feedback mechanism with weight matrices using non-linear matrix and ii) measuring the eigenvectors to obtain the probability rate of classification. Inspired by the time series model, the proposed method Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) is designed for forest detection with higher accuracy and minimum complexity.

CONCLUSION

In this paper, a method for fire detection is presented. By modeling both the presence of the fire using local and global descriptors of spatiotemporal features and the histogram mean evaluation of the pixels' intensities in a video database through statistical and histogram analysis, we showed that high fire detection accuracy is said to be achieved while reducing the false positive alarms. The use of the

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Multivariate Robust Regressive model with the Fully Recurrent Neural Learning Classifier increases the robustness of the algorithm by exploiting multiple extracted features and classifying them according to the output function to measure the probability that the eigenvectors belong to each class. The benefits of reduce the computational complexity than the existing fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2]. To improve the fire detection accuracy and false positive alarms with minimum time complexity, MR-FRNC is introduced. Fully Recurrent Neural Learning Classifier is used to improve the fire detection performance. Experimental results with two hundred and fifty video frames containing both fire and non-fire videos showed that the proposed method outperforms existing state-of-the-art methods. In future, the work of our proposed work is also proceed using wavelet preprocessing to extract fire features and remove the complexity involved in fire detection. In addition, future work is focused to analyze more parameters to get better performance of the proposed technique.

CONFLICT OF INTEREST
The authors declare no conflict of interest.

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None.

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No financial support was received to carry out this project.

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