Efficient Disaster Management through Perona Malik Deep Convolutional Classification

M.Nirmala[1], V.Saravanan[2], T. Seeni Selvi[3], K.Vigneshkumar[4]

[1,4] *Assistant Professor, Department of Computer Applications, Hindusthan College of Engineering and Technology, India*

E-mail: nilarangan@gmail.com[1], krishvigneshkumar@gmail.com[4]

[2]*Professor and Head, Department of Information Technology,*

[3]*Associate Professor, Department of Computer Science, Hindusthan College of Arts & Science, India*

E-mail: vsreesaran@gmail.com[2], seenurajan24@gmail.com[3]

Abstract

Predicting natural disasters like floods can help people mitigate their impact. When it comes to managing the aftermath of natural disasters like cyclones and wildfires, satellite photos are an incredibly useful resource. Classification methods are developed to categorise affected areas in order to furnish relevant and timely information for disaster response. A Perona-Malik Deep Convolutional Classification (PMRCC) Method is suggested for faster and more accurate disaster identification in this study. When it comes to catastrophe management, PMRCC does three distinct things: pre-processing, segmentation, and classification. To begin, the provided dataset is used to determine the number of satellite photos. Before processing the input raw pictures, the Perona-Malik Diffusion model is applied. Images with noise can nevertheless have their edges, lines, and details preserved because to the pre-processing model's careful design, which allows for their interpretation. We use probit regressive segmentation to separate the preprocessed picture findings. In order to divide the images into several sections, the segmentation procedure uses pixel similarity determination. Finally, Cophenetic Deep Convolutional Neural Learning Classification is used to categorise the segmented images as either disastrous or non-disastrous. Here, in order to correctly categorise the input photos, the correlation between the training set of images (the segmented ones) and the testing set of images (the disastrous or non-disastrous ones) is calculated. This is how the PMRCC approach to disaster management works. In comparison to existing methods, the suggested PMRCC approach significantly reduces classification time and error rate while simultaneously improving classification accuracy, according to the study's results.

Keywords: Disaster Management, Perona–Malik Diffusion, Probit Regressive Segmentation, Cophenetic Deep Convolutional Neural Learning, Satellite Images

1. Introduction

Satellite imagery is an enormously important resource for disaster management and response. This imagery can then be used to identify damaged areas that need the most support and also routes that are still accessible for evacuation and emergency responses. Recently, Artificial intelligence (AI) technologies have been designed for disaster management with satellite images. The main advantage of deep learning for classification tasks is that the entire system is trained to provide ultimate classification results with minimum time.

Hybrid deep learning (ConvLSTM) algorithm was introduced in [1] by combining a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Network for flood forecasting. ConvLSTM algorithm determines the future incidence of the flood. But, noise removal was not performed to accurately find the flood. A segmentation neural network was developed in [2] to distinguish the regions and available roads in disaster situations. ImageNet was applied for aerial image segmentation. ImageNet enhanced the segmentation performance for diverse models but, the segmentation accuracy was not improved.

Adaptive forest fire points detection model was designed in [3] using Three-Dimensional Otsu. The model robotically finds potential forest fire points based on the histogram of brightness. Despite forest fire points being specified, the error rate was reduced. A new multimodal deep learning framework was developed depending on the Multiple Correspondence Analysis in [4] for disaster management. But, the results of the classification were not improved.

A two-level fusion method was introduced in [5] to determine the building irregularity in post-disaster. The designed method was fast enough to support save and rescue missions. The false positive rate was reduced in irregularity detection but, the time consumption was not minimized. An object-based classification was developed in [6] to assess marine disaster vulnerabilities. But, the classification accuracy was not at the required level.

A novel 3-dimensional (3D) CNN- Recurrent neural network (RNN)-based earthquake detector was described in [7] to get effective disaster response. The designed method provided good robustness and generalization ability, but the response time was not focused to be minimized. In [8], hybrid Adaboost-Multi-layer Perceptron (MLP) neural networks were designed to discover the fire proficiently. The hybrid model finds the fire in videos or images but, the prediction time was not decreased.

The Federated transfer learning approach was introduced in [9] for disaster classification. But, the performance of classification was not enhanced. A deep neural network (DNN) model was introduced in [10] to simplify cost trends in natural disaster aspects. However, disaster management was not effective. To solve the above-mentioned issues, a novel method is designed for disaster management.

2. Literature Survey

A novel scenario scheme for many hazard disasters combining experiment–simulation–field data and tools have been developed [11]. Though accurate prediction was attained, the time for disaster detection was not reduced. Deep neural network architecture was designed in [12] to find the variations between stable and flooded water regions by exploiting the temporal differences amid flood events extracted by different sensors. But, the time needed for flood mapping was not focused.

Change Vector Analysis (CVA) referred to as ORCHESTRA (autOecodeR-based CHange dEtection in hyper SpecTRAl/ multispectral images) was designed [13] to observe the satellite images for Earth's scene analysis. However, the noise removal process was carried out. A new method to robotically find emergency data from social media disaster images was described in [14]. Though the type of disaster was determined, image quality was not improved.

Deep Learning (DL) algorithms were reviewed in [15] to provide timely disaster response with multi-source multimodal data. Though the algorithms were analyzed with their benefits, the performance of disaster management was not analyzed. Semi-automatic classification was presented in [16] to outline geohazard areas with satellite imagery. But, the noise removal was not carried out to provide better outputs.

The drought trend analysis was carried out in [17] based on mean duration, mean spatial extent, and frequency. The drought evolution process was applied to describe the evolution of drought type into another type. A blockchain-based framework was introduced to improve the current drought risk management system. However, the computational cost was not reduced by drought trend analysis. In [18], semi-automated detection and characterization method was employed to flood analysis. But, an accurate analysis was not made.

EmergencyNet-based Efficient Aerial Image Classification was designed in [19] for Drone-Based Emergency Monitoring. But, the error rate was significantly reduced. Machine learning algorithms and U-Net were designed in [20] to find the Landslide in the Himalayas. However, the detection performance was not efficient since the deep learning model needs better-quality images for processing.

3. Methodology

In this section, Perona–Malik Regressive based Cophenetic Deep Convolutional Classification (PMRCC) Method is designed to efficiently classify satellite images for disaster management. The proposed PMRCC comprises three different processes namely preprocessing, segmentation, and classification for better disaster management. The block diagram of the PMRCC method is shown in Figure 1.

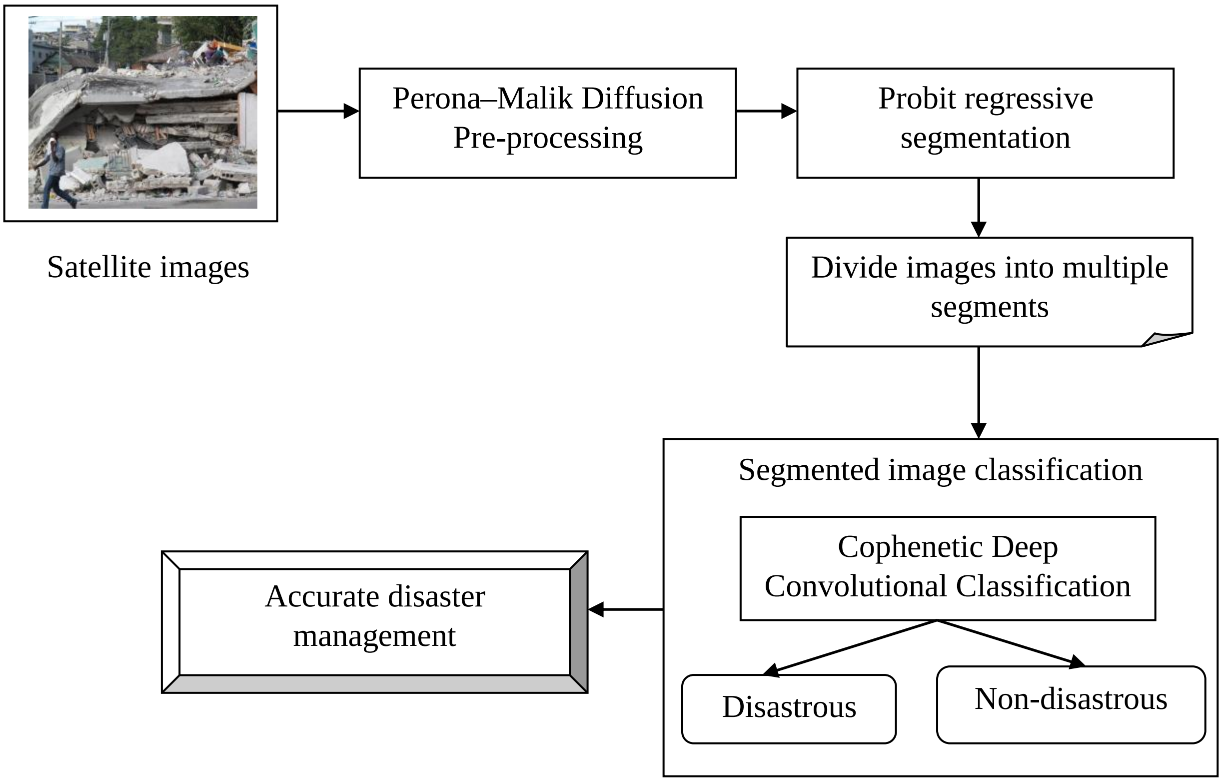

Figure 1 Block diagram of Perona–Malik Regressive based Cophenetic Deep Convolutional Classification

Figure 3.1 illustrates the process involved in the PMRCC method for disaster identification. A number of satellite images are taken as input from a given database. PMRCC method performs three processes. First, the satellite images are preprocessed using the Perona–Malik diffusion model using eradicating noise in the image without affecting contents like edges, lines, etc. The preprocessed images are subjected to the segmentation process for segmenting images into several regions by identifying background and foreground pixels. Lastly, Cophenetic deep convolutional neural learning is applied to classify the segmented images into disastrous or non-disastrous images with better accuracy and lesser time.

- **Perona–Malik Diffusion based Pre-processing Model**

The proposed PMRCC method initially carry out image preprocessing to enhance the image quality. The raw input image has noise and redundant content. The processing of noisy images provides inaccurate results. Hence, the proposed PMRCC method utilizes Perona–Malik diffusion filtering to eradicate the noise without concerning the image content.

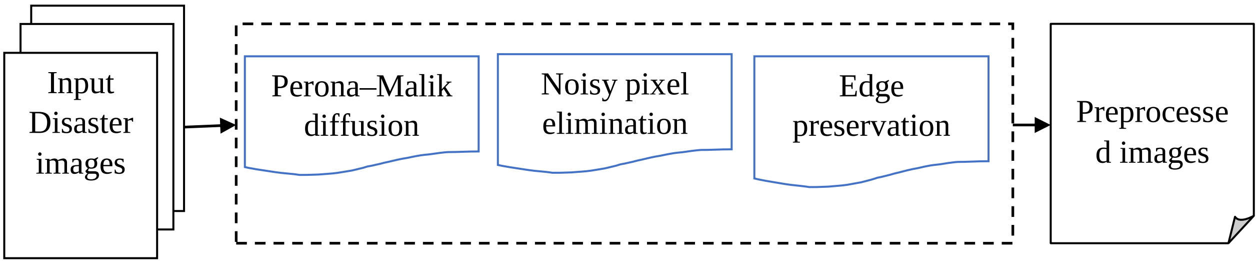

Figure 2 Perona–Malik diffusion based Pre-processing Model

Figure 2 shows the process of disaster image preprocessing using Perona–Malik diffusion filtering. By using the filtering model, a significant element of the images such as edges, and lines are not concerned for further processing. Consider the input image and the pixels are represented by $a_{1,}a_2, a_3, \dots a_n$. The pixels in the images are sorted in a filtering window with the size of 3*3 in the diversity of rows and columns. By using Perona–Malik diffusion filtering, the pixels are sorted in a filtering window in increasing order. Then, the center value is considered from the filtering window. The proposed filtering is associated with Gaussian within the non-linearity for achieving the preprocessed image is mathematically expressed as follows.

$$\frac{\partial I}{\partial t} = d_o(\varphi(|CG \times I|)\nabla I) \quad (1)$$

Where, 'I' denotes a sample original input image, 'd_o' is a divergence operator, 'φ' diffusion coefficient to protect image edges, 'C' is a conductance function to manage the diffusion strength, '∇I' is the gradient form of an image to preserve the edges and 'G' is a Gaussian distribution and it is mathematically given by,

$$G = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{{a_i}^2 + {a_m}^2}{2\sigma^2}\right)} \quad (2)$$

Where, 'σ' refers to a deviation, 'a_i' is a pixel in window and 'a_m' is a middle (center) pixel in the window. By using the above observation, the pixels that are deviated from the middle value are referred to as noisy pixels. Noisy pixels are eliminated from the filtering window. Therefore, the edges in the images are preserved to enhance the image quality. The pseudo-code representation of the Perona–Malik diffusion-based pre-processing model is given below.

Input: Disaster Image dataset 'DS' with number of images '$I = I_1, I_2, .., I_n$, pixels $p_1, p_2, p_3, \dots . p_m$ **Output**: Achieve higher leaf image quality for disease prediction

Begin
Acquire plant leaf images $I_1, I_2, I_3, \dots . I_n$ as input
For each plant leaf images I_i
Sort the pixels $p_1, p_2, p_3, \dots . p_m$ in the filtering window
Compute the center value p_c
Estimate likelihood between the center and neighboring pixels 'β'
Detect the noisy pixels
Take away noisy pixels from the filtering window
Get quality enhanced image
End for
End

Algorithm 1 Perona–Malik diffusion based Pre-processing Model

As given in the above algorithm, Perona–Malik diffusion is applied to eradicate the noise presented in the disaster image without affecting the image content such as edges and lines. This can be achieved by applying Gaussian distribution in the preprocessing model where it computes the likelihood among the pixel and their nearby pixels in the window. With this, noisy pixels are eliminated to get the edge-enhanced image results.

Probit Regressive Segmentation

With the results of preprocessed images, segmentation is carried out to segment the images into multiple parts. In the PMRCC method, probit regression is applied to perform image segmentation with better accuracy. Probit regression is a statistical analysis that finds the association between pixels in the pre-processed image. In this work, the jaccard index is applied to determine the association between pixels for segmenting the images into multiple segments.

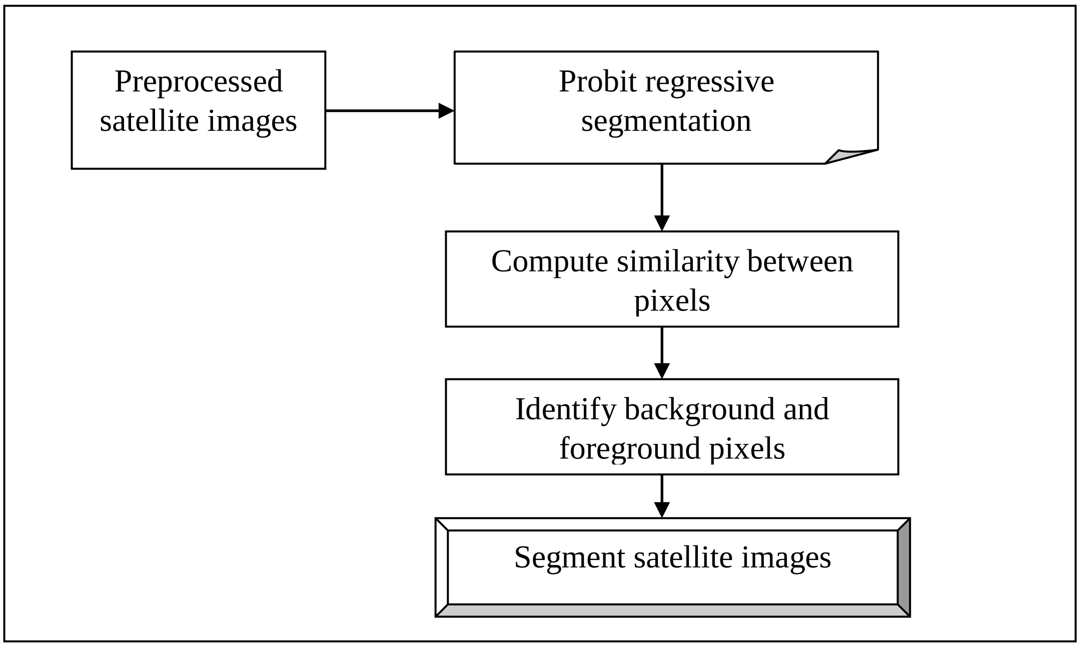

Figure 3 Probit Regressive Segmentation

Figure 3 depicts the process of probit regressive segmentation to segment the preprocessed satellite images $PI = PI_1, PI_2, .., PI_n$ into multiple segments by computing the similarity between the pixels. Jaccard index is mathematically computed as follows.

$$S_J = \left(\frac{a_i \cap a_n}{\sum a_i + \sum a_n - a_i \cap a_n}\right) \quad (3)$$

Where 'S_J' is a Jaccard similarity index, 'a_i' is an image pixel, 'a_n' is a neighbouring pixel of image, the intersection symbol '$\cap$' refers a mutual dependence between the two pixels, '$\sum a_i$' refers a sum of 'a_i' score, '$\sum a_n$' refers a sum of 'a_n' score. Followed by this, threshold value (i.e., 0.5) is set for the jaccard similarity index to determine the foreground and background pixels for segmenting the images into multiple segments. It is given by,

$$y = \begin{cases} S_J > T_h ; & FP \\ S_J < T_h ; & BP \end{cases} \quad (4)$$

Where 'y' is an output of segmentation and 'T_h' is a threshold value. Based on the above equation, the results of a similarity index higher than the threshold are identified as foreground pixel 'FP' and it is considered for segmentation. Besides, the similarity index lesser than the threshold is identified as background pixel 'BP' and it is avoided for disaster detection. In this way, accurate segmentation is achieved in the PMRCC method with higher accuracy. The pseudo-code representation of probit regressive segmentation is described as follows.

Input: Preprocessed images $PI = PI_1, PI_2, .., PI_n$
Output: Accurate disaster image segmentation

Begin
For each preprocessed disaster image PI_i
Apply regression analysis
Compute similarity between pixels 'S_J' using (3)
If $S_J > T_h$ **then**
Identify the pixel is foreground pixel
End if
If $S_J < T_h$ **then**
Identify the pixel is background pixel
End if
Segment the images into different regions
End
End

Algorithm 2 Probit Regressive Segmentation

As given in the above probit regressive segmentation algorithm, background and foreground pixels are determined to perform segmentation for disaster image identification. First, preprocessed images PI_i are used as input. Then, the probit regression is applied to find the pixel similarity using the jaccard similarity index. The threshold value is set to distinguish the foreground and background pixels where the foreground pixels are taken as significant to carry out the segmentation accurately for disaster management.

Cophenetic deep convolutional neural learning Classification

By considering segmentation results, classification of disastrous and non-disastrous image is performed for identifying disaster in an accurate way. In proposed PMRCC method, cophenetic deep convolutional neural learning is applied is employed to classify the each segmented images into diverse classes. Cophenetic deep convolutional neural learning comprises three different kinds of layers such as input layer, hidden layer and output layer.

Hidden layers comprises a layer to carry out the convolution operation whereas the input of segmented images are contributes to input of the next layer. The architecture of Cophenetic deep convolutional neural learning is shown in Figure 4.

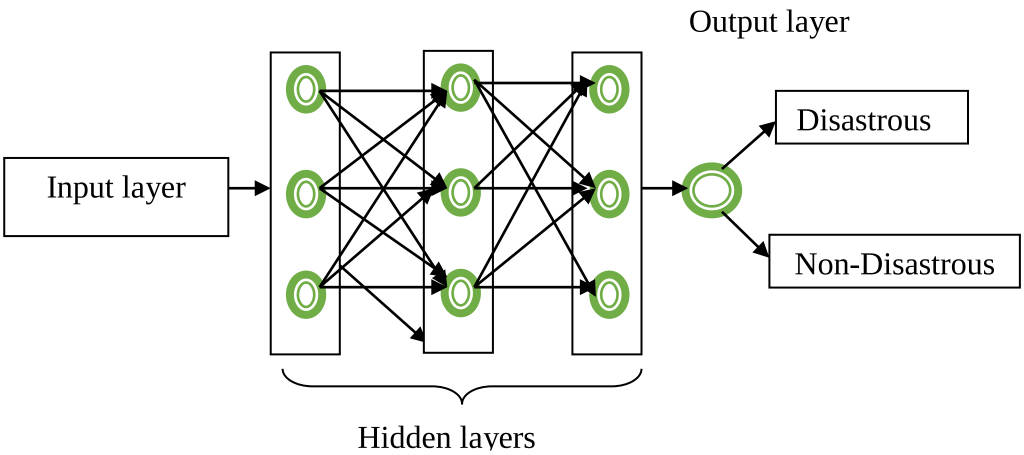

Figure 4 Structure of Cophenetic deep convolutional neural learning

Figure 4 shows the structure of Cophenetic deep convolutional neural learning for classifying the segmented images with multiple layers. As given in the above figure, each layer comprises number of neurons and is completely associated with another layer by using variable weight. The network comprises input, hidden, and output layers. Number of segmented satellite images $SI_1, SI_2, SI_3, \dots .SI_n$ is used as input in the input layer. Thus, the neural activity in the input layer is formulated as follows.

$$i(t) = \vartheta + (\sum_{i=1}^{n} SI_i(t) * \omega_1) \qquad (5)$$

Where '$i(t)$' is a neural activity at the input layer, 'ω_1' is a weight, '$SI_i(t)$' is an input segmented image and 'ϑ' is a bias. The inputs are further sent to the hidden layers where Cophenetic correlation is applied to measure correction between the segmented input image and testing image (i.e., disastrous or non-disastrous image) to classify the segmented images into two different classes. Hence, the Cophenetic correlation is computed as follows.

$$C_p = \frac{\sum_{i=1}^{n}(SI_i - \overline{SI})(TI_i - \overline{TI})}{\sqrt{\sum_{i=1}^{n}(SI_i - \overline{SI})^2 \sum_{i=1}^{n}(TI_i - \overline{TI})^2}} \qquad (6)$$

Where 'C_p' is a Cophenetic correlation coefficient, 'SI_i' is a training image (i.e. segmented image), 'TI_i' is a testing image, '$\overline{SI}$' is an average of the training image, and '$\overline{TI}$' is an average of the testing image. The results of Cophenetic correlation are varied as -1 to +1 where +1 indicates two images are statically similar and '-1' indicates two images are not similar. Thus, the output of the hidden layer is provided as follows.

$$h(t) = \sum_{i=1}^{n} \omega_1 * SI_i(t) + (\omega_2 * h\,(t-1)) \qquad (7)$$

Where '$h(t)$' denotes an output of hidden layer, 'ω_2' denotes the weight of the hidden layers '$h(t-1)$' is an output of the previous hidden layer, and operator '$*$' refers to a convolutional operator. The results of the Cophenetic correlation are given to the output layer for obtaining the final classification output. In the output layer, the tanh activation function is applied to classify the images and it is mathematically expressed as below.

$$o(t) = \tau(\omega_3 * h(t)) \quad (8)$$

Where $o(t)$ indicates the activity of neurons at the output layer, ω_3 indicates a weight of the hidden and output layer, $h(t)$ indicates an output of the hidden layer and τ is a tanh activation function and it is given by,

$$\tau = \frac{e^{C_p} - e^{-C_p}}{e^{C_p} + e^{-C_p}} \quad (9)$$

$$\tau = \begin{cases} +1; & disastrous\ image \\ -1; & non - disastrous\ image \end{cases} \quad (10)$$

By using activation function results, input images are classified for disastrous identification. Lastly, the error rate is measured for each classified result and it is given by,

$$E_r = \tau - \delta \quad (11)$$

Where, 'E_r' is an error rate, 'τ' is a predicted output of classification using the activation function and 'δ' is the actual output of the classification process. Based on the error rate, the weights are updated, and find the minimal error results for disaster detection.

$$f(x) = arg\,min\,E_r \quad (12)$$

When the learning model achieves minimum error, the process is terminated. With this, accurately classified results for disaster management are achieved with maximum accuracy and minimum time. The pseudo-code representation of Cophenetic deep convolutional neural learning classification is given below.

Input: Disaster Images Dataset 'DS', Segmented images $SI_1, SI_2, SI_3, \ldots. SI_n$

Output: Efficient classification of disaster images

Begin
Take segmented images as input in input layer (5)
Forward inputs SI_i to hidden layers
For each input SI_i
Compute Cophenetic correlation 'C_p' using (6)
Send C_p results to output layer using (8)
Apply tanh activation function 'τ' using (9)
If $(\tau = +1)$ **then**,
Classify the image as $disastrous$
End if
If $(\tau = -1)$ **then**,
Classify the image as $non - disastrous\ image$
End if
Estimate error rate E_r using (11)
Find minimum error results $f(x) = arg\,min\,E_r$
End for
End

Algorithm 3 Cophenetic deep Convolutional Neural Learning Classification

Algorithm 3 illustrates the process of Cophenetic deep convolutional neural learning to enhance the accuracy of disaster image classification. First, the segmented images are given to the input layer. Second, a Cophenetic correlation is applied to find the relationship between training and testing images. Based on the correlation results, images are classified in the output layer with smaller error for disaster management.

4. Experimental setup

Simulation of the proposed PMRCC method and existing ConvLSTM algorithm [1] and segmentation neural networks [2] are implemented using MATLAB. The performance of disaster management using above mentioned methods is analyzed by using disaster image datasets gathered from https://www.kaggle.com/mikolajbabula/disaster-images-dataset-cnn-model. The dataset comprises 4500 images that can be classified into four disaster categories cyclone (928 images), earthquake (1350 images), flood (1073 images), and wildfire (1077 images). These input images are preprocessed, segmented, and finally classified to find disastrous and non-disastrous images. For providing simulation work, the number of satellite images in the range of 50 to 500 images is taken as input. The experimental purpose of the proposed method is to achieve higher accuracy in image classification with a minimized time and error rate. Performance of both proposed and existing methods are analyzed under the testing metrics as follows.

- Classification accuracy
- Classification time
- Error rate

5. Discussion

In this section, simulation results of the proposed PMRCC method, existing ConvLSTM algorithm [1], and segmentation neural networks [2] are described in terms of three different performance metrics. The obtained results of the proposed PMRCC method are compared with the existing [1] and [2] to show the effectiveness of the method in disaster management. The comparative analysis is provided in terms of tables and graphs.

Classification Accuracy Performance analysis

Classification accuracy is defined as the percentage of disaster imagery from satellites that are appropriately labelled as either disastrous or non-disastrous, relative to the total number of input satellite images taken from the image dataset. In order to achieve effective catastrophe management, classified satellite photos are utilized. It is measured in percentage (%) and it is mathematically formulated as below.

$$CA = \sum_{i=1}^{n} \frac{I_{CA}}{I_i} * 100 \qquad (13)$$

Where 'CA' is classification accuracy and it is computed depending on the images taken in the simulation 'I_i', and images classified accurately 'I_{CA}'. The method with higher accuracy is consistent for disaster management. A comparison of classification accuracy for three different methods is demonstrated in table 1.

Table 1 Impact of Classification Accuracy

Number of images	Classification accuracy (%)		
	Existing ConvLSTM algorithm	Existing segmentation neural networks	Proposed PMRCC method
50	85.00	83.00	93.00
100	84.00	82.00	91.64
150	83.00	80.00	90.00
200	82.00	78.62	89.00
250	81.62	76.31	87.00
300	76.25	74.21	86.00
350	73.61	70.36	85.63
400	71.13	69.14	84.00
450	69.52	67.00	83.00
500	67.14	65.14	82.14

The accuracy of satellite image classifications with respect to varying numbers of images is compared in Table 1. Using a satellite image from the dataset allows for comparison to be accomplished. For the experimental purpose we have taken 50 to 500 images from the disaster satellite dataset. The above table shows the comparison result of proposed PMRCC method with existing ConvLSTM algorithm by Mohammed Moishin et al., (2021) and segmentation neural networks by Ananya Gupta et al., (2021) respectively. Hence, accuracy on classifying disastrous and non disastrous images using the proposed method is higher when compared to other existing methods mentioned here.

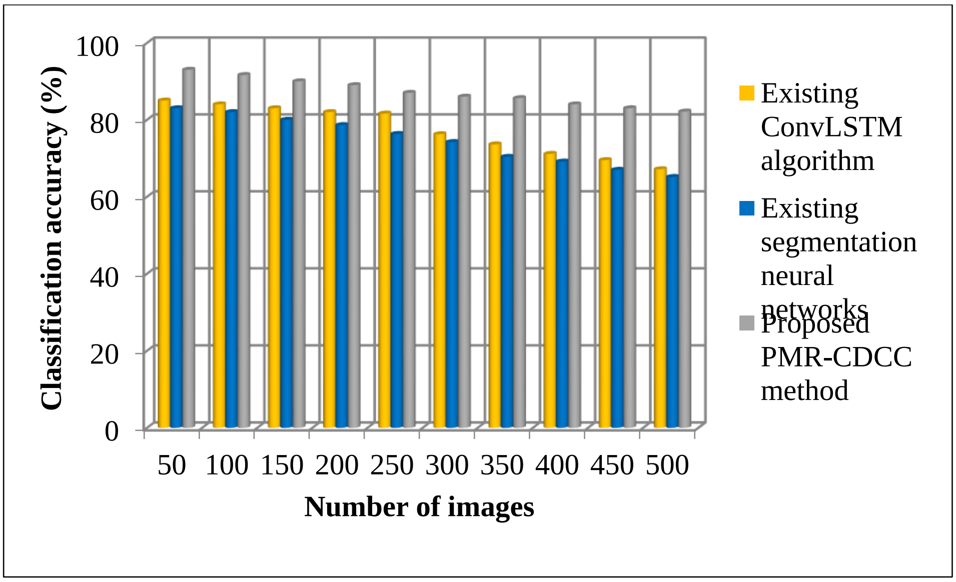

Figure 5 Performance result of classification accuracy

The performance result of classification accuracy for the proposed and existing methods is presented in Figure 5. With respect to satellite images, accuracy in classifying images is obtained. According to the results of the experimental analysis, the proposed method provides higher accuracy in image classification than the existing methods. For instance, a total of 50 satellite images are considered to provide a simulation result. From there, the PMRCC method attains 93% accuracy, whereas the ConvLSTM algorithm and segmentation neural networks obtain 85% and 83% of accuracy, respectively. But comparatively, the PMRCC method attains higher classification accuracy as compared to other existing methods for efficient disaster management.

The proposed PMRCC method classifies disastrous and non disastrous images effectively by applying cophenetic deep convolutional neural learning Classification algorithm. Based on the measured cophenetic correlated coefficient value, the images are correctly classified with a minimum error. In addition, tanh activation function is presented to accurately classify satellite images as disastrous and non- disastrous. Thus, image classification is carried with improved accuracy. From the result analysis, proposed PMRCC method increases classification accuracy by 13% and 17% when compared to existing methods namely ConvLSTM algorithm by Mohammed Moishin et al., (2021) and segmentation neural networks by Ananya Gupta et al., (2021) respectively.

Experimental analysis of classification time

Classification time is defined as the amount of time it takes to divide images from satellites into two categories: those containing catastrophic events and those without. The time needed to categorize a disaster image is dependent on both the quantity of input photographs and the time consumed by each individual image. It is calculated using the following formula and expressed in milliseconds (ms):

$$C_{Time} = I_i * Time(CSI) \qquad \text{…… (14)}$$

From the above equation (14), Classification Time 'C_{Time}' is measured based on 'I_i' the number of input images. The time taken to classify a single image is represented as '$Time(CSI)$'.

Table 2 Experimental values of classification time

Number of images	**Classification time (ms)**		
	Existing ConvLSTM algorithm	**Existing segmentation neural networks**	**Proposed PMRCC method**
50	27	32	22
100	30	35	26
150	33	38	28
200	36	41	32

250	39	45	35
300	43	49	38
350	45	53	40
400	48	56	42
450	52	61	45
500	55	65	48

The above table 2 illustrates the experimental result of classification time on the satellite image that obtained while classifying disaster images from input images. For experimental purpose, the number of input images is considered in the range of 50 to 500 images from disaster satellite images dataset. Based on considered input images, comparison of the proposed PMRCC method is made with existing methods namely ConvLSTM and segmentation neural networks. When compared to state-of-the-art works, the simulation results shows suggested method achieves minimum time to categorize satellite images.

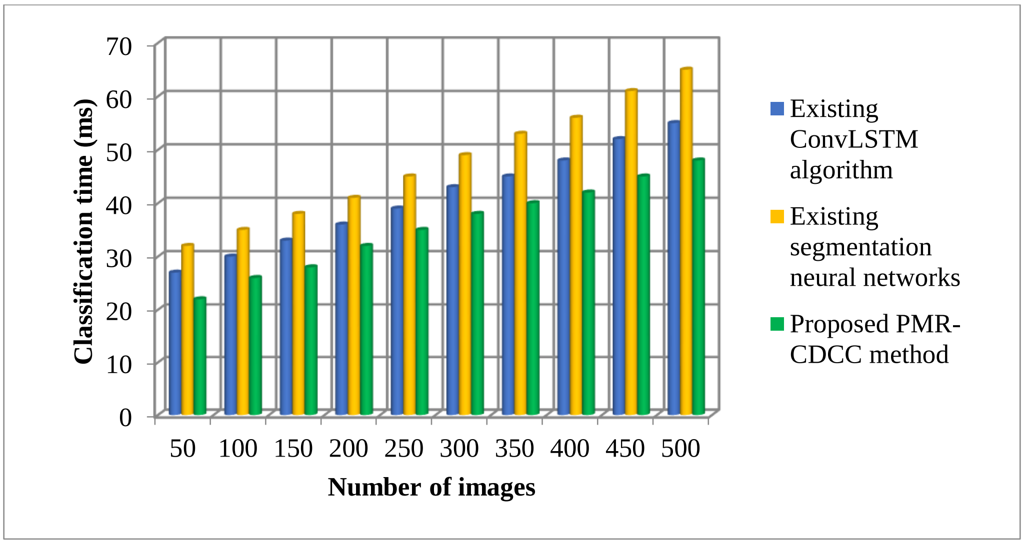

Figure 6 Experimental result of classification time

The result of the experimental analysis on classification time is described in the above figure 5.6 according to the different number of input images from the satellite image dataset. For the experimental purpose, different numbers of input images ranging from 50 to 500 images are considered. Figure 1 shows the experimental results of the time taken to classify images using the proposed method compared with existing methods such as the ConvLSTM algorithm and segmentation neural networks. Here, the existing ConvLSTM algorithm and segmentation neural networks attain 27 ms and 32 ms of time, respectively, whereas the proposed PMRCC method achieves 22 ms of classification time. Besides, while varying the input images for detecting disaster images, the time taken for the classifier process is also getting varied using all methods. As a result, the PMRCC method resulted in a shorter classification time than the other methods.

Initially, the Perona-Malik diffusion model is applied to raw input images to eliminate noise data, and processed data is attained. Probit regressive segmentation is performed for separating images into different segments. At last, cophenetic deep convolutional neural learning is performed to classify the segmented images into different classes. By measuring the phenetic correlation coefficient value, disastrous and non-disastrous images are effectively classified. With a classified result, the time for image classification is effectively minimized. Hence, the proposed PMRCC method minimizes the classification time by 13% and 25% when compared to existing methods, namely the ConvLSTM algorithm by Mohammed Moishin et al. (2021) and segmentation neural networks by Ananya Gupta et al. (2021), respectively.

5.4.3 Impact of error rate

The error rate is calculated by dividing the number of satellite images that are wrongly labelled as catastrophic or non-disastrous by the total number of images that were input from the dataset. Its formula and measurement in percentage (%) are as follows:

$$ER = \frac{I_{incorrectly\ classified}}{I_i} * 100$$

…. (15)

From the equation (15), error rate is estimated and represented as 'ER'. In above expression, '$I_{incorrectly\ classified}$' denotes the number of incorrectly classified satellite images and 'I_i' specifies the total number of input satellite images.

Table 3 Tabulation of error rate

Number of images	Error rate (%)		
	Existing ConvLSTM algorithm	**Existing segmentation neural networks**	**Proposed PMRCC method**
50	15.00	17.00	7.00
100	16.00	18.00	8.36
150	17.00	20.00	10.00
200	18.00	21.38	11.00
250	18.38	23.69	13.00
300	23.75	25.79	14.00
350	26.39	29.64	14.37
400	28.87	30.86	16.00
450	30.48	33.00	17.00
500	32.86	34.86	17.86

The above table 3 shows the simulated values of the error rate that occurred during the image classification process with respect to the different number of input images. For experimental purposes, a number of satellite images in the range of 50 to 500 images is considered. We conduct the simulation by comparing proposed and existing methods. Here, the proposed PMRCC method is compared with existing methods such as the ConvLSTM algorithm by Mohammed Moishin et al. (2021) and segmentation neural networks by Ananya Gupta et al. (2021). According to the number of satellite images, the error rate gradually varied. Thus, the PMRCC method minimizes the error rate during disaster management compared to the other existing methods.

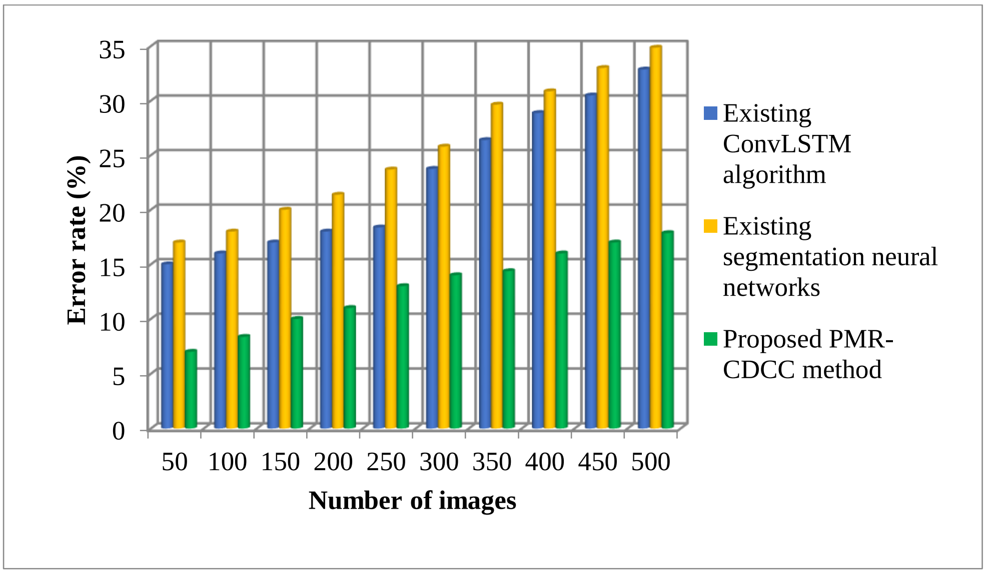

Figure 7 Measure of error rate

Figure 7 describes the comparison result for the error rate with respect to various numbers of images. Here, images with a range of 50 to 500 images are considered for 10 iterations. The effectiveness of disaster management on satellite images using the PMRCC method is verified by comparing it with existing methods. The compared methods are the ConvLSTM algorithm and segmentation neural networks. For example, a satellite image of 400 is taken as input for simulation purposes. From the conducted simulation results, the PMRCC method achieves 7% of the error rate, whereas 15% and 17% of the error rate are attained using the ConvLSTM algorithm and segmentation neural networks. Three methods significantly minimize the error rate when increasing input images. As compared to other existing methods, the PMRCC method attains a better result in terms of reduced error rate.

By applying Cophenetic Deep Convolutional Neural Learning, satellite images are analyzed for efficient disaster management. Here, segmented satellite images are considered input. The phenetic-correlated coefficient value is estimated between training and testing images. Based on measured correlated values, images are effectively classified as disastrous and non-disastrous. Then, the Tanh activation function is presented to achieve a classification result with a minimized error rate. Therefore, the PMRCC method reduces the error rate for enhanced disaster management by 43% and 50% when compared to existing methods such as the ConvLSTM algorithm by Mohammed Moishin et al. (2021) and segmentation neural networks by Ananya Gupta et al. (2021).

6. Conclusion

In this paper, a novel method called PMRCC is presented to manage the disaster with satellite images. PMRCC is designed with a deep learning concept for classifying satellite images in a faster manner. To get the quality-enhanced images for further processing, Perona–Malik Diffusion model is applied to preprocess the input images and thereby increase the image quality. Probit regressive segmentation is applied to segment the images into multiple segments based on the measuring similarity between pixels. Lastly, Cophenetic Deep Convolutional Neural Learning Classification is used to analyze the segmented images with testing images for classifying images into disastrous and non- disastrous. An experimental assessment is carried out to analyze the performance of the PMRCC method with conventional classification methods using diverse metrics. The results verified that the proposed PMRCC method achieves better performance in terms of higher accuracy, lower time, and error rate than the existing methods.

References

[1] Mohammed Moishin, Ravinesh C. Deo, Ramendra Prasad, Nawin Raj, and Shahab Abdulla, "Designing Deep-Based Learning Flood Forecast Model With ConvLSTM Hybrid Algorithm", IEEE Access, Volume 9, 2021, Pages 50982 – 50993

[2] Ananya Gupta, Simon Watson, Hujun Yin, "Deep learning-based aerial image segmentation with open data for disaster impact assessment", Neurocomputing, Elsevier, Volume 439, 7 June 2021, Pages 22-33

[3] Zhao Deng and Gui Zhang, "An Improved Forest Fire Monitoring Algorithm With Three-Dimensional Otsu", IEEE Access, Volume 9, 2021, Pages 118367 – 118378

[4] Samira Pouyanfar, Yudong Tao, Haiman Tian, Shu-Ching Chen, Mei-Ling Shyu, "Multimodal deep learning based on multiple correspondence analysis for disaster management", World Wide Web, Springer, volume 22, 2019, Pages 1893-1911

[5] Mohammad Kakooei, Yasser Baleghi, "A two-level fusion for building irregularity detection in post-disaster VHR oblique images", Earth Science Informatics, Springer, volume 13, 2020, Pages 459-477

[6] Fengshuo Yang, Xiaomei Yang, Zhihua Wang, Chen Lu, Zhi Li, Yueming Liu, "Object-based classification of cloudy coastal areas using medium-resolution optical and SAR images for vulnerability assessment of marine disaster", Journal of Oceanology and Limnology, Springer, Volume 37, 2019, pages 1955–1970

[7] Muhammad Shakeel, Katsutoshi Itoyama, Kenji Nishida, Kazuhiro Nakadai, "Detecting earthquakes: a novel deep learning-based approach for effective disaster response", Applied Intelligence, Springer, Volume 51, 2021, Pages 8305-8315

[8] Faisal Saeed, Anand Paul, Won Hwa Hong, Hyuncheol Seo, "Machine learning based approach for multimedia surveillance during fire emergencies", Multimedia Tools and Applications, Springer, Volume 79, 2020, Pages 16201-16217

[9] Zehui Zhang, Ningxin He, Dongyu Li, Hang Gao, Tiegang Gao, Chuan Zhou, "Federated transfer learning for disaster classification in social computing networks", Journal of Safety Science and Resilience, Elsevier, Volume 3, Issue 1, March 2022, Pages 15-23

[10] Ji-Myong Kim, Sang-Guk Yum, Hyunsoung Park, Junseo Bae, "A deep learning algorithm-driven approach to predicting repair costs associated with natural disaster indicators: The case of accommodation facilities", Journal of Building Engineering, Elsevier, Volume 42, October 2021, Pages 1-7

[11] Rui Ba, Qing Deng, Yi Liu, Rui Yang, Hui Zhang, "Multi-hazard disaster scenario method and emergency management for urban resilience by integrating experiment–simulation–field data", Journal of Safety Science and Resilience, Elsevier, Volume 2, Issue 2, June 2021, Pages 77-89

[12] Georgios I. Drakonakis; Grigorios Tsagkatakis; Konstantina Fotiadou; Panagiotis Tsakalides, "OmbriaNet—Supervised Flood Mapping via Convolutional Neural Networks Using Multitemporal Sentinel-1 and Sentinel-2 Data Fusion", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Volume 15, 2022, Pages 2341 - 2356

[13] Giuseppina Andresini, Annalisa Appice, Daniele Iaia, Donato Malerba, Nicolo Taggio, Antonello Aiello, "”Leveraging autoencoders in change vector analysis of optical satellite images, Journal of Intelligent Information Systems, Springer,Volume 58, 2022, Pages 433–452

[14] Amna Asif1* , Shaheen Khatoon1 , Md Maruf Hasan1 , Majed A. Alshamari1 , Sherif Abdou4 , Khaled Mostafa Elsayed2 and Mohsen Rashwan, "Automatic analysis of social media images to identify disaster type and infer appropriate emergency response", Journal of Big Data, volume 8, Springer, 2021, Pages 1-28

[15] Nilani Algiriyage, Raj Prasanna, Kristin Stock, Emma E. H. Doyle, David Johnston, "Multi-source Multimodal Data and Deep Learning for Disaster Response: A Systematic Review", SN Computer Science, Springer, Volume 3, 2022, Pages 1-29

[16] Karma Tempa, Komal Raj Aryal, "Semi-automatic classifcation for rapid delineation of the geohazard-prone areas using Sentinel-2 satellite imagery", SN Applied Sciences, Springer, volume 4, 2022, Pages 1-14

[17] Vikas Poonia, Manish Kumar Goyal, B.B. Gupta, Anil Kumar Gupta, Srinidhi Jha and Jew Das, "Drought occurrence in Different River Basins of India and blockchain technology based framework for disaster management", Journal of Cleaner Production, Elsevier, Volume 312, August 2021, Pages 1-15

[18] Kushanav Bhuyan, Cees Van Westen, Jiong Wang, Sansar Raj Meena, "Mapping and characterising buildings for food exposure analysis using open-source data and artifcial intelligence", Natural Hazards, Springer, 2022, Pages 1-31

[19] Christos Kyrkou, and Theocharis Theocharides "EmergencyNet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutional Feature Fusion" IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Volume 13, 2020, Pages 1687-1699

[20] Sansar Raj Meena, Lucas Pedrosa Soares, Carlos H. Grohmann, Cees van Westen, Kushanav Bhuyan, Ramesh P, Singh, Mario Floris, Filippo Catani, "Landslide detection in the Himalayas using machine learning algorithms and U-Net", Landslides, Springer, volume 19, 2022, pages 1209–1229