



**Article Title: High-Performance Deep Learning Classifier for Predicting Cyclones Based On Rain Optimization Algorithm**

## **High-Performance Deep Learning Classifier for Predicting Cyclones Based On Rain Optimization Algorithm**

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### **ABSTRACT**

One of the most potent and devastating types of weather phenomena on Earth are tropical cyclones (TC). A cyclone is a large air mass that revolves in a powerful epicenter of low atmospheric pressure, rotating counterclockwise in northern hemisphere and clockwise in southern hemisphere. In this work, a unique deep learning model for predicting the path of tropical cyclones is proposed. Unlike previous predictions, cyclones have the potential to cause serious harm to both individuals and their possessions. To lessen the adverse impacts of cyclones, better and more precise prediction systems are required. In order to anticipate cyclones, this work proposes an efficient Rain Optimized Convolutional Neural Network (RO-CNN). The input image is manipulated and preprocessed using Notch filter. Grey Level Coordination Matrix (GLCM) is utilized for gathering the features from segmented output after the processed image and it is fed into K-means clustering technique for segmentation. When compared to other conventional methods, the proposed classifier achieves higher levels of accuracy in classification. In order to validate its effectiveness, suggested ROA-CNN based system is implemented in MATLAB platform and accuracy obtained during classification using ROA-CNN is about 95.8%.

**Keywords:** Rain optimization algorithm, Tropical cyclones, Convolutional neural network, Grey level Coordination Matrix, Notch filter.

### **1 Introduction**

Warm cyclonic circulations known as tropical cyclones form across the tropical and subtropical seas. TCs are considered extreme weather occurrences that have potential to cause significant damage in coastal regions all over the world. Over the duration of the past decade, a large number of weather forecasters and warning organisations have dedicated themselves to this research, leading to technology improvements, atmospheric boundary layer, interactions of atmospheric environment, growth in physics, ocean responses and approaches for forecasting [1]. The majority of the cyclone dynamical detection models typically has less accuracy, which



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is partly because depiction of intricate physical processes, TCs' vortex initialization and coarse resolution are insufficient [2]. In recently, scientists started applying Machine Learning (ML) to enhance forecasting abilities of TCs in order to address these issues with traditional methods. According to the tasks they are used for ML algorithms are often categorized into three groups: feature selection, clustering, and regression or classification [3]. In place of manually created features, deep learning employs a deep architecture with many processing layers made up of linear or nonlinear transformations combining hierarchical feature extraction and automatic feature learning [4]. Forecasters have used satellite data to provide early warnings for the development of cyclones; nevertheless, a large portion of the results were relied on human judgment, which is outdated in the present age. Statistical models and other alternatives cannot handle the complex and nonlinear relationship between TC-related components, necessitating further development of their predicting results [5].

In this regard, a typical Tucker decomposition method solves dynamical problems that classical Tensor Decomposition Algorithm (TDA) unable to accomplish. [6]. Hierarchical clustering [7] and the Finite-Mixed Model (FMM) [8] are two examples of popular clustering techniques. These algorithms, however, are extremely sophisticated and unable to repair corrupted data bases. In this work, k-mean algorithm is proposed due to its efficiency in implementing segmentation. The best features are extracted by combining k-means with GLCM [9], and the primary objective of feature extraction is to identify the features that are the best representations of an image and have the fewest parameters. Finding the appropriate features helps speed up the diagnosis of cyclone because non-essential aspects in cyclone photos have been successfully removed. Two exemplary algorithms that can successfully handle nonlinear problems by establishing kernel functions are Support Vector Machine (SVM) for accurate classification purpose [10] and Support Vector Regression (SVR) for regression [11]. In addition, Decision Tree (DT) [12] is a widely used method which accurately extract and present categorization rules.

Artificial Neural Network (ANN) [13] conducts a complicated mathematical formulation from a very fundamental idea of an information processing cycle in order to produce the best outcome for every dataset or issue segment. However, for large neural networks, a lot of processing time was required. In this work, CNN is employed for classification process which requires less time consumption with high accuracy. A Typhoon-Resilient Single-Family House's Structural Orientation as well as Roof Angle are optimized by applying Genetic Algorithms and Calculated Fluid Dynamics is proposed in [14]. The work in [15] suggested a detection model for cyclone forecast based on SVM with Particle Swarm Optimization (PSO-SVM) to change threshold linearly a conventional precipitation method is employed in order to increase predictability of precipitation. In this paper, Rain Optimization algorithm (ROA) is utilized for enhancing performance of neural networks accuracy in classification. The benefaction of this study is listed in the following;



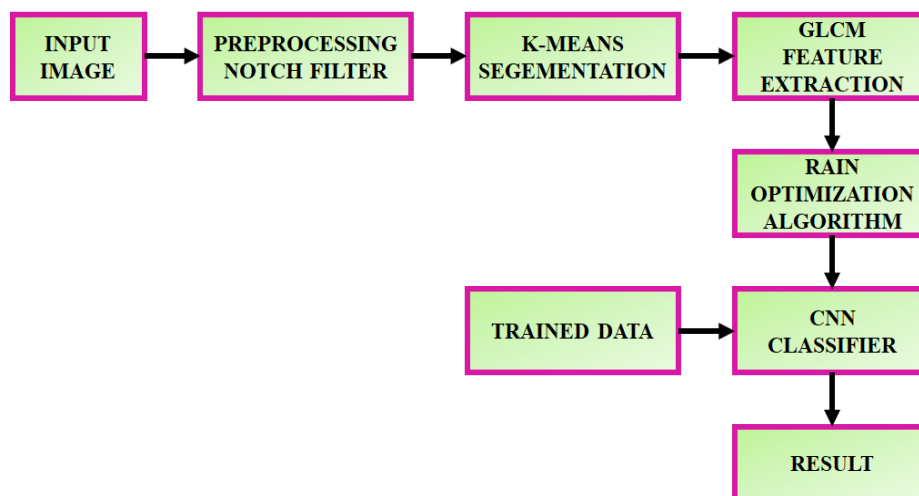
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- Notch filter is utilized to perform preprocessing that eliminates an isolated frequency or a limited range of frequencies.
- K-means algorithm is utilized for segmentation process which resolves issues in clustering.
- Feature extraction is performed using GLCM which define an image's appearance and draws features from it.
- ROA-CNN is utilized for classification purpose that improves classifiers precisions.

Overall system is executed in MATLAB platform and classification accuracy is observed effectively based on the outcomes obtained.

## 2 Proposed System Modelling

The fundamental block diagram showing the way input images are processed and extracted is shown below Figure 1.



**Figure 1: Proposed Model**

The adaptive notch filter receives the cyclone image at first to perform pre-processing, which involves removing noise from the images. Without compromising the clarity of the image, the filter used removes the speckling noise. The image are segmented and a average value produced for every cluster in K means clustering, which is the next step in segmenting the noise-free image. Due of the intricacy, time commitment, and memory consumption, GLCM performs feature extraction. Following an accurate cyclone detection, the image is subsequently classified utilising CNN.

### 2.1 Preprocessed by Notch Filter

To reduce the noise in images, unprocessed images are processed before getting employed. Pre-processing is a technique intended to lessen the impact of reflection , speckle noise and



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other associated characteristics in images. Among of the pre-processing methods, filtering helps to improve images by removing image noise. When undesirable signals are reduced while the desired signal is maintained, a filter is said to be efficient. In advance of recognising an object, picture improvement and filtering techniques are used to reduce the image's deteriorating interference from impulsive noise. The quantity and intensity of the noise influence the kind of filter that should be applied to the image for best results. In this method, the grayscale image's undesired noise has been hidden by using a notch filter. This filter preserves borders and boundaries while relying on the pixel value. By beginning with the pixel values in sequential order and replacing the observed pixel with the centre value, the notch filter is approximated. The image's speckle noise is removed without compromising sharpness.

## **2.2 Segmented by K-means Clustering**

Following pre-processing, K-means clustering is used as an analysis of clustering components. K-means clustering is a multidimensional statistical approach used to divide data into uniform subgroups and segment it based on similarities. The primary concept behind K-means is to assign each cluster a central point, that's the average of the cluster values. The K-means technique's stages are listed as follows.

1. Select the centers of K clusters in the beginning, then continue performing processes 2 and 3 up until the cluster membership stabilizes.
2. Generate another partition by sending every data set to the closest cluster nodes.
3. Calculate the cluster midpoint by taking the newly formed cluster center into consideration.

Cluster analysis, preprocessing and post processing are additional steps in the segmentation method. As a result, the extraction of features is done after K-means clustering is used to segment cyclone images.

## **2.3 Feature Extraction by GLCM**

It is a method of gathering additional information regarding an image, like shape, colour, texture and contrast. In reality, texture analysis is a essential element of both visual perception of humans and machine learning systems. By choosing key features, it could be employed to increase the diagnostic system's precision.. This is one of the more popular GLCM and texture feature evaluation applications. This method extracts features from the cyclone images in two stages. The GLCM is obtained in the initial stage, and the texture characteristics depending on the GLCM are determined in the second step. The following is a collection of a number of the important features' statistics feature formulas.

### *2.3.1 Contrast*

It is an estimation of the degree of pixel-to-pixel variation in the image. Equation 1 gives an equation for determining contrast.



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$$\text{Contrast} = \sum_{i=1}^L \sum_{j=1}^L [i - j]^2 \times \text{GLCM}(i, j) \quad (1)$$

### 2.3.2 Correlation

It evaluates the linear connection between an image's greyscale values. Equation 2 is the correlation computation formula.

$$\text{Corr} = \sum_{i=1}^L \sum_{j=1}^L \frac{(i - \mu_i)(j - \mu_j)(\text{GLCM}(i, j))}{\sigma_i \sigma_j} \quad (2)$$

Where,

$\mu$  = mean

$\sigma$  = Standard Deviation

$$\mu_i = \sum_{i=1}^L \sum_{j=1}^L i * (i, j)$$

$$\mu_j = \sum_{i=1}^L \sum_{j=1}^L j * (i, j)$$

$$\sigma_i = \sqrt{\sum_i^L \sum_j^L (i - \mu_i)^2 \text{GLCM}_{i,j}}$$

$$\sigma_j = \sqrt{\sum_i^L \sum_j^L (j - \mu_j)^2 \text{GLCM}_{i,j}}$$

### 2.3.3 Energy

Equation 3 is capable of being used to determine the overall amount of colour consistency in an image.

$$\text{Energy} = \sum_{i=1}^L \sum_{j=1}^L \text{GLCM}(i, j)^2 \quad (3)$$

### 2.3.4 Homogeneity

It is the difference in the image based on GLCM close proximity. Equation 4 can be used to compute the homogeneity.

$$\text{Homogeneity} = \sum_{i=1}^L \sum_{j=1}^L \frac{\text{GLCM}(i, j)}{1 + |i - j|} \quad (4)$$

### 2.3.5 Entropy

Use the variable components of GLCM for expressing the size of the grey level inconsistency in a picture. Equation 5 can be used to compute entropy.

$$\text{Entropi} = - \sum_{i=1}^L \sum_{j=1}^L \text{GLCM}(i, j) \log \text{GLCM}(i, j) \quad (5)$$



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## 2.4 Rain algorithm Optimized CNN Classifier

### 2.4.1 Rain Optimization Algorithm

In this research, the ROA is used to reduce the complexity of CNNs, as well as to optimize the parameters of CNN. ROA is applied as a verification technique to computerized demanding benchmark tasks. ROA imitates the way raindrops naturally fall, flowing from a high point down into a valley. Raindrop behavior is the primary source of motivation for ROA. Raindrops fall gradually from mountains down slopes, forming rivers that always flow to the lowest spots on land or emptied into the ocean.

### 2.4.2 Mathematical Model ROA

RFO begins with a base populations represented by raindrops. The drop number DN is determined by the formula below if a population size is  $Z$ ;

$$DN = V_{m,1}, V_{m,2}, V_{m,3} \dots \dots V_{m,n} \quad (6)$$

$$m \in \{1,2,3 \dots \dots Z\} \quad (7)$$

$V$  is the variable in the optimization challenge, while  $n$  is the number of optimization parameters.

The optimization procedure handles raindrops in the form of rain-fall. It is produced using a uniform random distribution function and is also impacted by all the restrictions listed in the formula follows.

$$V_{m,n} = Uni(UI_n, LI_n) \quad (8)$$

Where the uniform distribution function is called  $Uni$ . Lower and upper bounds of  $n$  are  $UI_n$  and  $LI_n$ . During optimization, A point in a drop's neighborhood is selected at randomized and is displayed as,

$$\left| |(DN - NP) \cdot \check{V}_n | \right| \leq ||R \cdot \check{V}_n \quad (9)$$

$$R = R(\text{initial} * \text{iteration}) \quad (10)$$

Here  $R$  is the actual positive vector encoding the decline in the neighborhood. The vector of units of the  $n$ th dimension is called  $NP$ . The dominant neighbor location DNP is a point that fulfils as stated by a formula between all the neighbor points of drop.

$$FD(DNP_m^n) < FD(NP^m) \quad (11)$$

$$FD(DNP_m^n) < FD(NP_m^n) m \in \{1,2,3 \dots \dots NP\} \quad (12)$$

The drop functions are  $FD$ . If a raindrop has not dominant neighbor points and its position is inactive, the optimization is performed to carry out the explosion method in order to help the drop escape this circumstance.

$$NP_{(\text{exp})} = NP * (EB) * EC \quad (13)$$

The total amount of neighbor points under ideal conditions with no explosions is  $NP_{(\text{exp})}$ . The terms "explosion base" and "explosion counter" are also used.



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In every iteration of the optimisation process, the positions of each raindrop are determined using the following equation.

$$OF_1 = FD|at\ n\ th\ iteration - FD|at\ 1\ st\ iteration \quad (14)$$

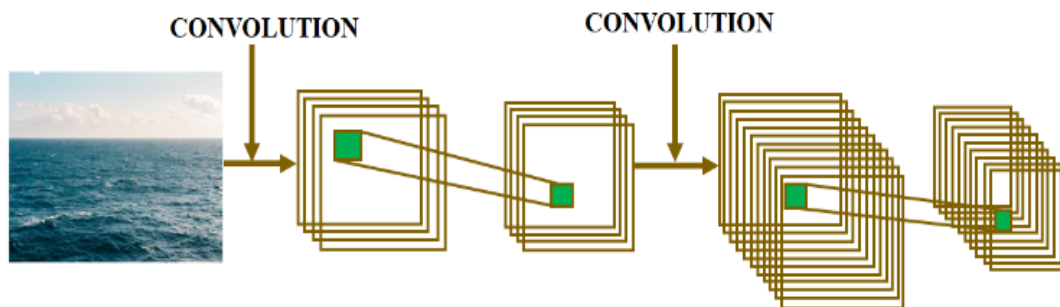
$$OF_2 = FD\ at\ nth\ iteration \quad (15)$$

$$Rank = \varphi_1 * order(OF_1) + \varphi_2 * order(OF_2) \quad (16)$$

Here the weighted coefficients  $\varphi_1$  and  $\varphi_2$  represent the  $OF_1$  &  $OF_2$  absolute change in the goal functions since the first iteration at iteration  $n$ .

### 2.4.3 CNN Classifier

For the categorization and identification of images, CNN is frequently utilized. Convolutional, pooling, and fully-connected layers make up the majority of all three of them. For the development of a full CNN model, these three layers are integrated. The convolutional layer consists of a set of trainable filters, the weights of which are determined automatically and then optimized. Figure 2 represents structure of CNN.



**Figure 2:** Architecture of CNN model

The dimension of space and system calculation time are then minimized by adding a max-pooling layer amid the convolutional layers. The output of the final max-pooling layer is sent to a layer that is fully connected for identification. This fully connected layer provides input image classification with the assistance of high-level characteristics gathered from the preceding layers, and it makes use of a softmax activation function at the output. Finally, the ROA-CNN implementation outperforms other conventional approaches, producing high-quality outputs with excellent precision.

## 3 Results and Discussion

To test the effectiveness of the recommended approach, MATLAB platform is employed. Figure 3 (a) and (b) show the input and cyclone image, respectively.

The normal and cyclone grey scale images are shown in Figure 4. Likewise Figure 5 shows how the noise in the normal and cyclone images has been decreased.



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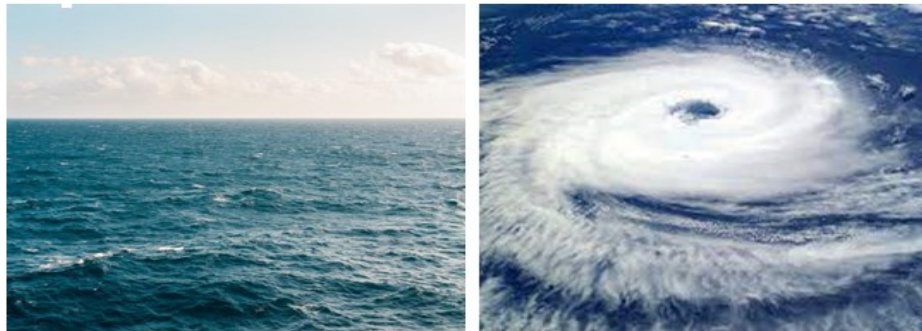


Figure 3: (a) Normal image (input image) (b) Cyclone image



Figure 4: (a) Gray Scale image for normal image and (b) cyclone image

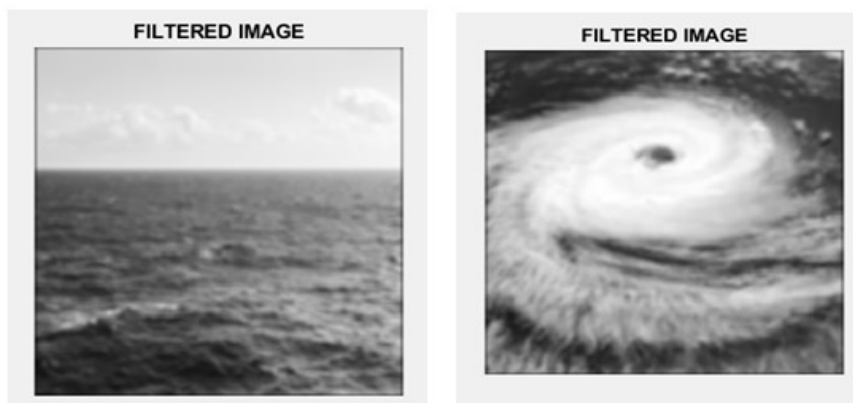


Figure 5: (a) Noise reduced normal image and (b) cyclone image



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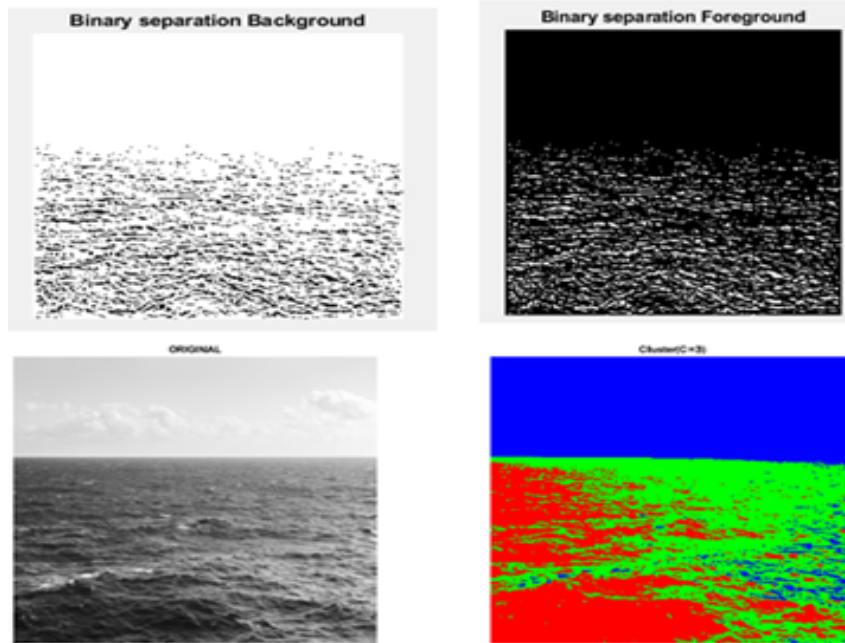


Figure 6: (a) Segmentation step output images for normal data

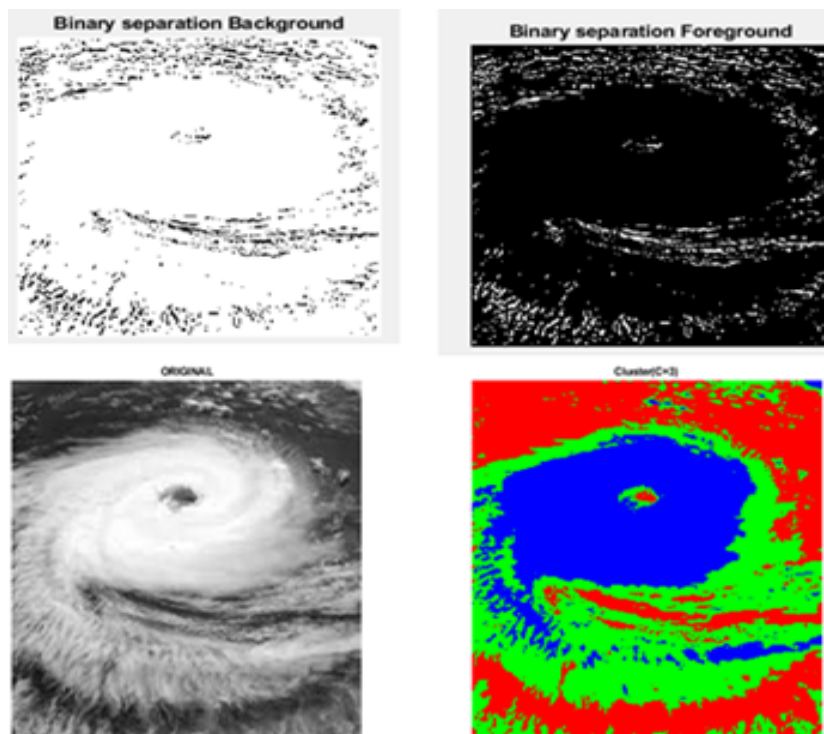
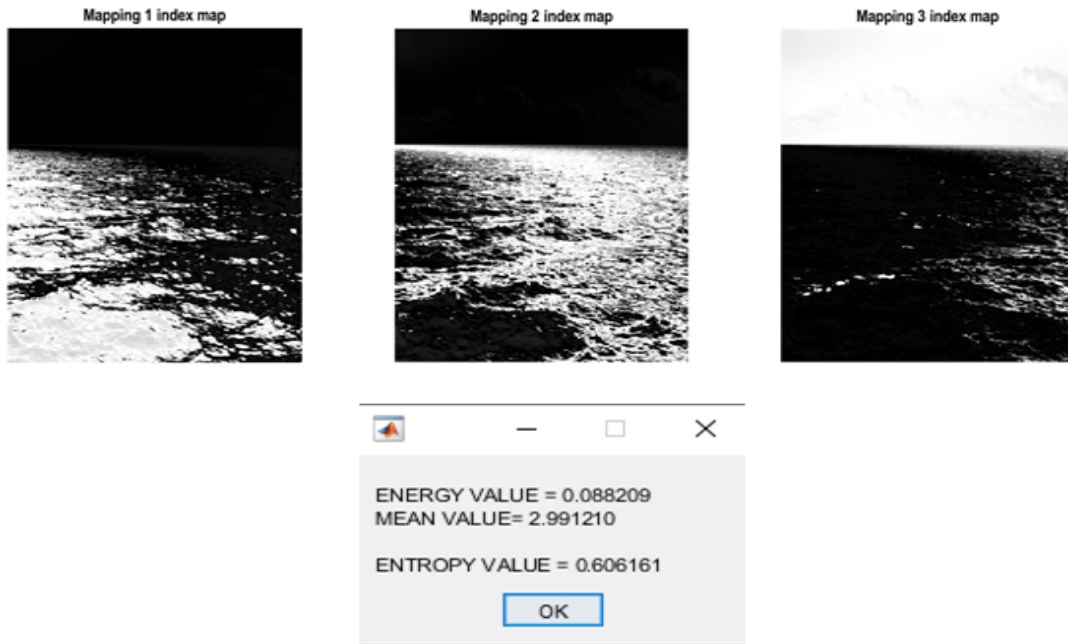


Figure 6: (b) Segmentation step output images for normal data

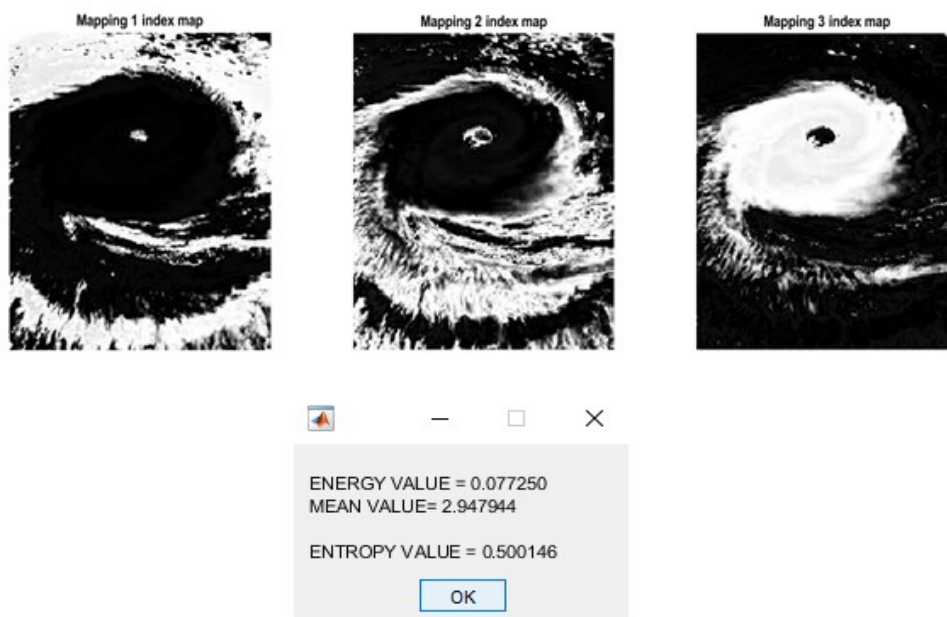


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The segmentation step's images of the output for normal and aberrant data are shown in Figure 6. The results of the GLCM for both normal and abnormal data are shown in Figure 7.



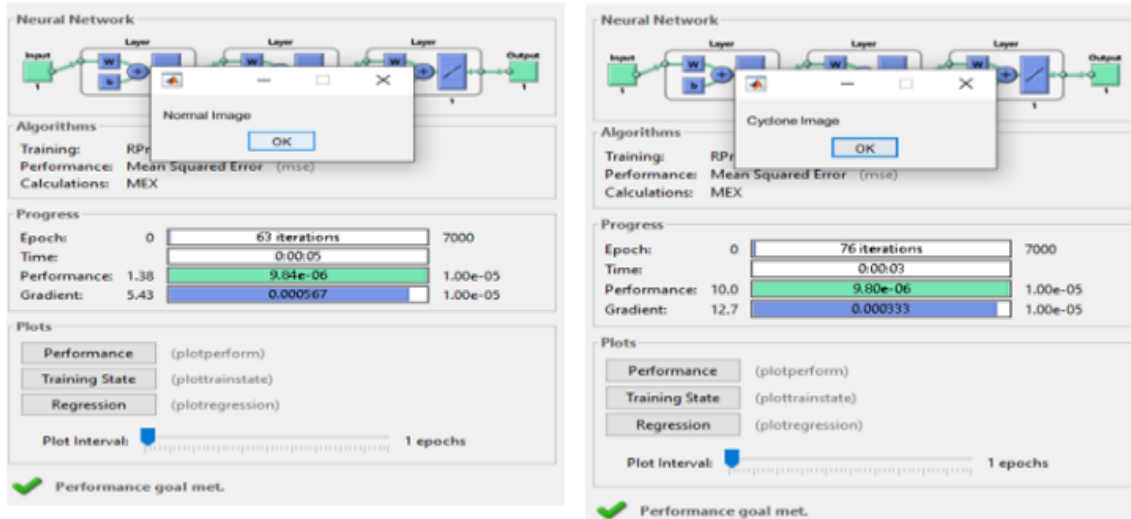
**Figure 7:** (a) *GLCM results for normal data*



**Figure 7:** (b) *GLCM results for abnormal data*



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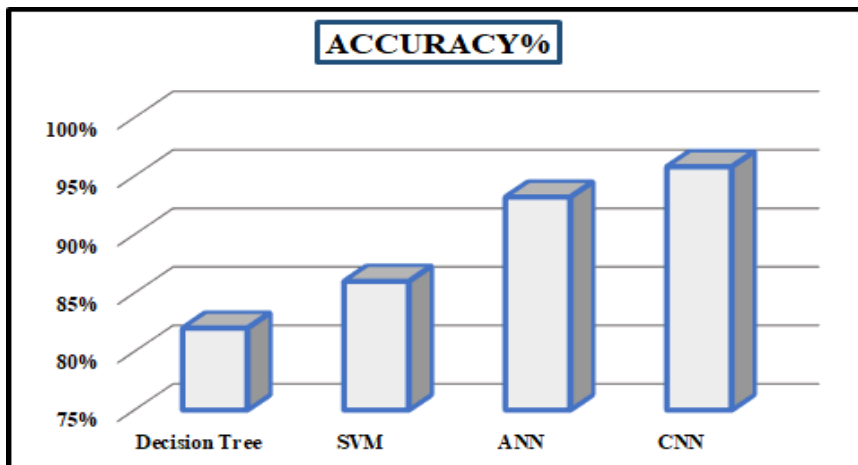


**Figure 8:** (a) & (b) Classification results for image 1&2

Figure 8 indicates the suggested classification results for normal and cyclone image.

**Table 1:** Comparison analysis of classification

Classification	Accuracy%
Decision Tree	82%
SVM	86%
ANN	93.2%
CNN	95.8%



**Figure 9:** Performance analysis of CNN



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Table 1 illustrates comparison analysis CNN with different classifier and the corresponding plot represented in Figure 9. From that plot, the suggested CNN classifier obtained high accuracy compared to other approaches such as, Decision Tree, SVM and ANN.

#### 4 Conclusion

Every year, natural disasters like tropical cyclones threaten all over the nation. According to data, cyclones damaged property, destroyed crops, and injured people along India's coastline. Cyclone forecasting is essential for both avoiding and minimizing significant harm. The methods employed rely on numerical models, which demand advanced knowledge and higher skill levels for making predictions with more level of accuracy. Therefore, in this work, Notch filter is utilized for preprocessing the input images and it is segmented and resized using K-means algorithm. Feature extraction is performed using GLCM and CNN classifier is employed for classification purpose and ROA is utilized to enhance the classification accuracy to predict cyclones occurrence. Finally, proposed system is executed in MATLAB software and effectiveness is observed with 95.8% accuracy in classification.

#### References

1. Kerry Emanuel, Year: 2018, "100 Years of Progress in Tropical Cyclone Research", Meteorol. Monogr., Vol: 59, pp. 15.1 – 15.68.
2. Year: 2020, "Tropical Cyclone Forecast Model", Available online: [https://en.wikipedia.org/wiki/Tropical\\_cyclone\\_forecast\\_model](https://en.wikipedia.org/wiki/Tropical_cyclone_forecast_model) (accessed on 1 May 2020).
3. Year: 2020, "Machine Learning", Available online: [https://en.wikipedia.org/wiki/Machine\\_learning](https://en.wikipedia.org/wiki/Machine_learning) (accessed on 9 April 2020).
4. C. E. Perez, Year: 2016, "Design Patterns for Deep Learning Architecture", [Online]. Available: <http://www.deeplearningpatterns.com/doku.php>.
5. Rui Chen; Weimin Zhang; Xiang Wang, Year: 2020, "Machine learning in tropical cyclone forecast modeling: A review", *Atmosphere*, Vol: 11, no: 7, pp. 676.
6. Jing-Yi Zhuo; Zhe-Min Tan, Year: 2021, "Physics-augmented deep learning to improve tropical cyclone intensity and size estimation from satellite imagery", *Monthly Weather Review*, Vol: 149, no: 7, pp. 2097 – 2113.
7. Chao Chen; Guanbin Li; Ruijia Xu; Tianshui Chen; Meng Wang; Liang Lin, Year: 2019, "Clusternet: Deep hierarchical cluster network with rigorously rotation-invariant representation for point cloud analysis", *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*.
8. Mohsen Maleki; Javier E. Contreras-Reyes; Mohammad R. Mahmoudi, Year: 2019, "Robust mixture modeling based on two-piece scale mixtures of normal family." *Axioms*, Vol: 8, no: 2, pp. 38.



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9. Jingliang Hu; Pedram Ghamisi; Xiao Xiang Zhu, Year: 2018, “Feature extraction and selection of sentinel-1 dual-pol data for global-scale local climate zone classification”, ISPRS International Journal of Geo-Information, Vol: 7, no: 9, pp. 379.
10. Nan Zhang; Mingjie Chen; Fan Yang; Cancan Yang; Penghui Yang; Yushan Gao; Yue Shang; Daoli Peng, Year: 2022, “Forest Height Mapping Using Feature Selection and Machine Learning by Integrating Multi-Source Satellite Data in Baoding City, North China”, Remote Sensing, Vol: 14, no: 18, pp. 4434.
11. Sachin Kumar; Zairu Nisha; Jagvinder Singh; Anuj Kumar Sharma, Year: 2022, “Sensor network driven novel hybrid model based on feature selection and SVR to predict indoor temperature for energy consumption optimisation in smart buildings”, International Journal of System Assurance Engineering and Management, pp. 1 – 14.
12. Sung-Hun Kim; Il-Ju Moon; Seong-Hee Won; Hyoun-Woo Kang; Sok Kuh Kang, Year: 2021, “Decision-tree-based classification of lifetime maximum intensity of tropical cyclones in the tropical western north pacific”, Atmosphere, Vol: 12, no: 7, pp. 802.
13. R. Joseph Manoj; M. D. Anto Praveena; K. Vijayakumar, Year: 2019, “An ACO–ANN based feature selection algorithm for big data”, Cluster Computing, Vol: 22, pp. 3953 – 3960.
14. Jun L. Mata; Jerson N. Orejudos; Joel G. Opon; Sherwin A. Guirnaldo, Year: 2023, “Optimizing Building Orientation and Roof Angle of a Typhoon-Resilient Single-Family House Using Genetic Algorithm and Computational Fluid Dynamics”, Buildings, Vol: 13, no: 1, pp. 107.
15. Jinglin Du; Yayun Liu; Yanan Yu; Weilan Yan, Year: 2017, “A Prediction of Precipitation Data Based on Support Vector Machine and Particle Swarm Optimization (PSO-SVM) Algorithms”, Algorithms, Vol: 10, no: 2, pp. 57.