International Journal for Modern Trends in Science and Technology, 9(04): 80-87, 2023

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0904013
Available online at: http://www.ijmtst.com/vol9issue04.html

High Performance Chicken Swarm Optimized Deep Learning Classifier for Cyclone Prediction

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To Cite this Article
A.T.R. Krishna Priya and Anuja.R. High Performance Chicken Swarm Optimized Deep Learning Classifier for Cyclone Prediction. International Journal for Modern Trends in Science and Technology 2023, 9(04), pp. 80-87. https://doi.org/10.46501/IJMTST0904013

Article Info
Received: 02 March 2023; Accepted: 28 March 2023; Published: 30 March 2023.

ABSTRACT

A cyclone is a massive air mass which rotates anticlockwise in the northern hemisphere and clockwise in the southern hemisphere within a powerful centre of low atmospheric pressure. Notwithstanding past projections, a cyclone has the power to significantly damage both people and property. Better and high accurate prediction methods are required to reduce the effects of cyclones. The variables from the traditional unsupervised classifiers need to be improved because they are less accurate. Thus, the aim of this paper is to propose an effectiveChicken Swarm Optimized Cascaded Deep learning Convolutional Neural Network (CSO-CDNN) is employed to predictthe cyclone. With the aid of Adaptive median filter, the input image is resized and preprocessed. The processed image is fed into Fuzzy C means (FCM) for segmentation and Grey Level Coordination Matrix (GLCM) is used to extract the features from segmented output. The CSO-CDNN is deployed to select the features from GLCM output, in order to increase the classification precision. The proposed classifier obtains the overall accuracy, when compared to other conventional approaches. The suggested CSO-CDNN classifier is implemented in MATLAB platform to validate its performance.

KEYWORDS: Cyclone prediction, Adaptive mean filter, CSO-CDNN, FCM, GLCM

1. INTRODUCTION

A cyclone is a type of natural disaster that happens when a low-pressure region forms over tropical waters and spins in a circular pattern, causing serious harm. It can also be referred to as a "typhoon" and its centre can rotate either clockwise or anticlockwise. Due to its destructive properties, including as extensive flooding, powerful winds, and intense downpours, it has caused innumerable damages all over the world [1].Tropical Cyclones (TC) are small, circular storms with winds swirling around a core of low air pressure. They typically have a diameter of 320 km (200 miles). The Coriolis force, a phenomena associated with the rotation of the Earth, as well as its low-pressure core are what propel the winds [2]. TC consequently rotate anticlockwise in the Northern Hemisphere and clockwise in the Southern Hemisphere.The TC genesis, intensity, and risk estimates in particular continue to present a number of issues with predicting abilities. The most widely used tropical cyclone dynamical forecast models typically have low accuracy, which is partly because TCs' vortex initialization, depiction of intricate physical processes, and coarse resolution are insufficient [3].

It's critical to comprehend cloud patterns in order to produce accurate findings [4]. Early warnings for cyclone development have been provided by forecasters using satellite data, however much of the results were based on human judgment, which is inefficient in the modern world. To get around some of the limitations in weather forecasting, researchers have employed machine learning and deep learning techniques. Nonetheless, more research is necessary to build a more trustworthy system.Moreover, alternative approaches, including statistical models, are unable to handle the intricate and nonlinear link between TC-related factors, necessitating additional improvement of their forecasting outcomes [5].In recent years, scientists started to think about applying machine learning (ML) to examine satellite, radar, in-situ data, etc. to improve the forecasting abilities of TCs in order to address these issues with traditional methods. According to their uses, machine learning algorithms can be categorized into three groups as an artificial intelligence (AI) tool: clustering, regression or classification, and feature selection.In order to improve job effectiveness and model correctness, feature selection algorithms can be used to remove pointless attributes using attribute selection.

A typical tucker decomposition method, for instance, can address spatio-temporal issues that the conventional tensor decomposition algorithm is unable to do that process [6]. One of the earliest techniques in pattern recognition and data mining, a clustering algorithm automatically categorizes a sample dataset into various groups. Big data analysis can use this in a variety of ways. The Finite-Mixed Model (FMM) [7], hierarchical clustering [8], and K-means method [9] are examples of common clustering algorithms.However, these algorithms has high complexity and inability to recover the data base corruption. By using FCM with GLCM, the best features are extracted and the main goal of feature extraction is to find the features that are the best representation of an image and have the fewest parameters. Because non-essential features in cyclone images have been successfully eliminated, the process of diagnosing cyclone can be completed faster by locating the right features.

Support Vector Machine (SVM) for classification [10] and Support Vector Regression (SVR) for regression [11] are two representative algorithms that can effectively deal with nonlinear problems by defining kernel functions. Furthermore, Decision Tree (DT) [12] is a common algorithm that can mine and display classification rules with high accuracy. The vast majority of mapping tasks are well performed by Artificial Neural Networks (ANNs) [13], CNNs [14] andRecurrent Neural networks (RNNs) [15], which are regarded as universal approximators for complex nonlinear mappings. However, these classifications are need high processing time. Here, the proposed CSO-CDNN attain high accuracy with low time consumption.

Therefore, the main contribution of this paper is to propose an effective optimized CDNN classifier for cyclone detection. By using Adaptive mean filter, the blurred input image is preprocessed. For segmentation FCM technique is used, the segmented image sample subjected into GLCM,it is extracting the high ranked features. The suggested classifiers obtain high accuracy compared other methods.

2. PROPOSED SYSTEM DESCRIPTION

Figure 1 illustrates schematic diagram for proposed cyclone prediction. Here, a CSO-CDCNN classifier is used to resolve the problems with current cyclone forecasting classifiers. The adaptive median filter is used to pre-process and resize the blurred input image to 256*256. The pre-processed image is segmented using FCM, and the GLCM is used to extract 12 texture features from the segmented output. CSO is employed to select features from GLCM results to improve classification accuracy.

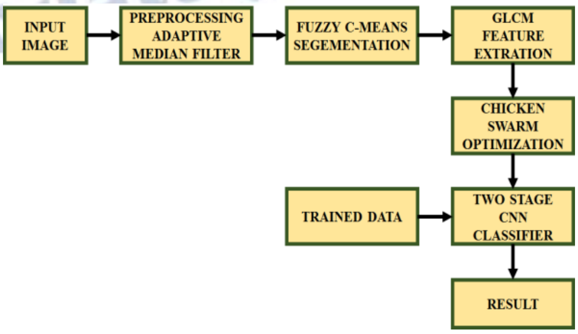

Figure 1 Block diagram

Finally, a two-stage Cascaded CNN classifier provides an efficient classification result for cyclone prediction. The performance of the proposed CSO-DCNN classifier is compared to that of conventional supervised and unsupervised classifiers.

1. Preprocessing by Adaptive Median Filter

A few significant compression techniques for cyclone identification in the cyclone image prediction system rely on interest areas. These pictures typically have low contrast and are noisy. Therefore, image demonizing is required to maintain the picture's performance through noise reduction. Noise makes the quality of the image and the feature extraction method unreliable. The extraction of features and noise removal techniques used in this study will improve the accuracy of image processing. In this study, a non-linear filter is used for demonizing. A method for picture improvement is filtering. Filtration can draw attention to some distinctive features or get rid of some undesirable features. The median filter performs nonlinear signal processing for signal assessment. The median filter preserves an image's edges while reducing background noise.

No imaging technique is noise-free, but some imaging techniques tend to have more noise than others. The interference is the one that occurs the most frequently. Spontaneous noise is introduced during the image acquisition and transmission processes. There are numerous sources of image noise. Miscommunication and computer vision can result in noise. The rectified pixel may use a grey value of 255 or 0 for salt and pepper noise. The noise that is dispersed throughout the image also results in changes to the information pixel, which may cause flailing in the visual data and quality. Median filters are used to remove noise from the pictures.

The grey level median in that pixel's community substitutes the pixel value, which the median indicates as the pixel value. Median filters fall under the umbrella of window - based operators. The output of median filters is assessed using a window, or neighbourhood of pixels. Windowing technicians carry out a procedure to determine the mean of each pixel in the surrounding area.

The origin pixel is the one that surrounds the window. The 55 pixel screen and correlating origin are shown in Figure 2.

-	-	-	-	-
-	-	-	-	-
-	-	**Origin**	-	-
-	-	-	-	-
-	-	-	-	-

Figure 2 Pixel window and origin

The pixel window is used to calculate the output median filters' results. These pixel windows can be any size and shape, though they tend to be odd numbers. The size of the proposed work is a 55 square because it is both large enough to work properly and small enough to produce an efficient image. The best interleaving controller is the median filter. The fundamental idea behind a median filter is to assess the random number of an input signal to see if it accurately represents the signal. In order to determine whether the signal is representative of the surrounding area or not, each pixel in the image is screened individually.

The median filter typically replaces pixel values with the median of those values rather than with the designated adjoining pixel value. It indicates that in the input cyclone images, the corresponding neighbourhood values are initially arranged in numerical order. The pixel value in question is then replaced with the median pixel value. In most cases, the input image's median filter runs using a frame that contains pixels with an odd amount of nodes. If the surrounding pixels in the image are even, the processed middle pixel value serves as the actual output for the median function. How the median filter functions in a screen is shown in the figure below.

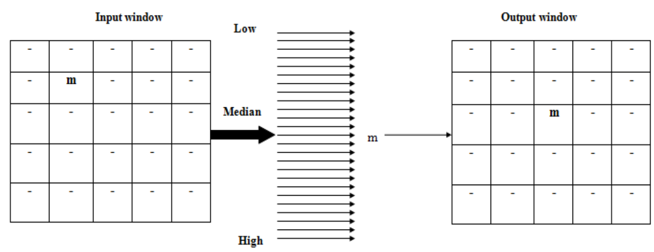

Figure 3 Graphical representation of median filter operation

The median value is chosen after sorting the window's pixel values in increasing order, as shown in Figure 3The median is the most reliable midpoint compared to the average value, which gives it the edge over other filters. The median value is unaffected by the neighborhood's non-representative pixels. As the filtration operates in the central area, it generates new, irrational pixel values based on the input picture. If a pixel falls within the specified range, it is not regarded to be manipulated and does not require processing. If it does not, however, it is determined to be manipulated and must be removed from the picture.

2. Fuzzy C Means Segmentation

Using fuzzy subscriptions, the FCM algorithm assigns pixels to each category. Let X = $(X_1 X_2, \ldots X_n)$ represent hyper spectral (features) data in the form of an image with n pixels that will be divided into $1 < c < n$ clusters. The FCM algorithm minimises the optimal solution defined as follows through iterative method.

$J_{FCM} = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^{m} ||x_i - v_k||^2$

(1)

With the following constraints

$\sum_{k=1}^{c} u_{ik} = 1,$ (2)

$0 \leq u_{ik} \leq 1, \forall i, and\ 0 < \sum_{i=1}^{n} u_{ik} < n, \forall k$

(3)

`Where v_k represents the prototype value of the kth cluster, u_{ik} represents the fuzzy membership of the iTh pixel with respect to the kth cluster and m is a parameter that controls the fuzziness of the clustering process.

With the aim of making things in similar classes similar and things in different classes fractious, clustering is a method for isolating details that concentrates into image samples or clusters. Specific connectedness initiatives may be used to classify things into groups, with the similitude indicator controlling how the groups are encircled, depending on the data's potential and the reasoning behind the clustering that is being used.

Several examples of actions that can be taken to gather join separation of the cyclone in an image. In hierarchical clustering, information is divided up into discrete groups, each of which corresponds to a single group from the cyclone images. In fuzzy clustering, data segments can be a part of much more than one grouping, and each section also comes with an affiliation level action plan.

3. GLCM feature extraction

Utilizing Gray Level Co-event Matrices (GLCMs), which have a place with quantifiable methodology in Cyclone analysis, is a noteworthy method for extracting features. The pixel intensities of a source images are second-arranged into measureable data of spatial association in the GLCM. The GLCM contains information about how commonly pixels with a grey level value of I j, introduced in an input cyclone image, occur either vertically, horizontally, or diagonally to neighborhood nodes with a value of i. An element called energy gauges how smoothly the input image moves.

The grey level co-occurrence matrix is a popular technique for extracting features. It has been a crucial technique for pixel pair partner computation in extracting features from images. The pixels that are co-occurring with the grey values I and j are listed in the co-occurrence matrix C i, j). N*N represents the co-occurrence matrix aspect.

Inertia $= \sum_i \sum_j (-j)^2\ c(i,j)$

(4)

Correlation $= \frac{\sum_i \sum_j (i-\mu_i)(j-\mu_j) c(i,j)}{\sigma_i \sigma_j}$

(5)

The combined probabilities of the specified pixel pair incidences are calculated.

Energy $= \sum_i \sum_j c(i,j)^2$ (6)

Energy in the matrix of co-occurrences at the grey level provides the sum of squares components sum.

Homogeneity $= \sum_{i,j} \frac{c(i,j)}{1+|i-j|}$

(7)

Therefore, the number of grey scales used for lossy compression determines how complicated a computation is. To reduce the dimensionality of the feature set, many components from the founder matrix are removed, including energy, connection, rigidity, and fractal dimension.

4. Chicken Swarm Optimization

The development of the chicken swarm intelligence was motivated by the social interactions of chickens, which are essential in establishing hierarchical order. In a flock, the dominant chickens will rule over the weaker chickens. Based on their gender, chickens exhibit different behaviors. When other chickens from other groups intrude on their region, the rooster, who serves as the leader of each group and actively searches for food, engages in combat. The rooster's head to food foraging would be more consistent if there were more dominant hens.

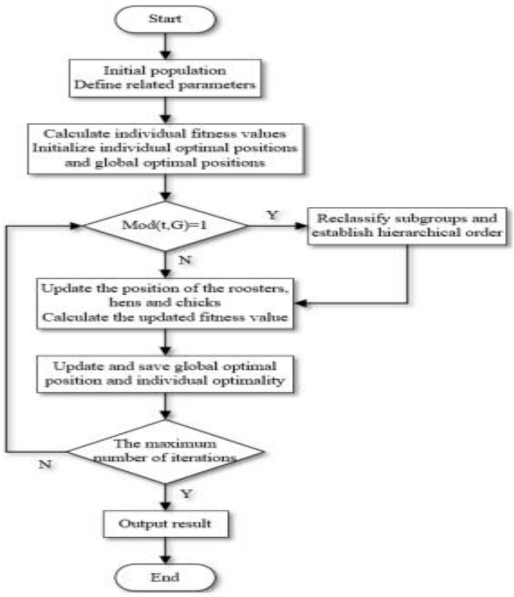

Figure 4 Flowchart of improving the chicken swarm optimization algorithm

The chickens that are subservient will forage for food away from the rest of the flock. Around their mother hen, the chicks actively seek food and cooperate with one another. In the power structure of the chicken swarm, the rooster is the leader, mom hens are co-leaders, hens are elders, and members of the swarm are chicks. This is illustrated in Figure 4, where the hierarchy is straightened from top to bottom according to fitness values.

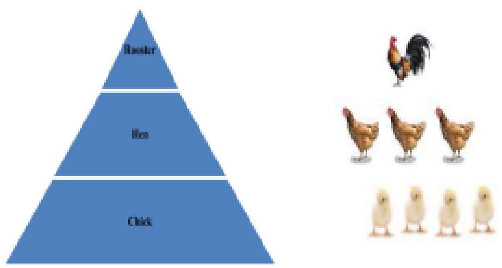

Figure 5 Chicken swarm Architecture

5. Two Stage CNN Classifier

Systems with convolutions typically, a structure consists of three different types of layers. Convolutional, accumulating, or totally affiliated layers are all possible. There are specific rules for forward and error backward signal propagation in each type of layer. There are no precise guidelines on how the composition of different layers should be. Although CNNs are typically divided into two sections, there are some exceptions, such as late progression. Convolutional and pooling layer mixtures are used in the first segment, referred to as extracting features. Categorization is the second phase, which makes use of layers that are entirely related.

Convolutional differ significantly from conventional fully connected neural network layers in that they preserve spatial structure. Using the 32 by 32 by 3 image as an example, the image is kept in its original 2D structure rather than being stretched to the one-dimensional vector of 3072 items. The input is changed into a distinct tensor known as an activation map by applying the convolutional filter, which also maintains internal structure. Stacking convolutional layers can be used to decrease the dimension of spatial data into a low-dimensional, feature-rich vector space where conventional fully connected networks can be applied because activation maps can be combined as well without losing spatial features.

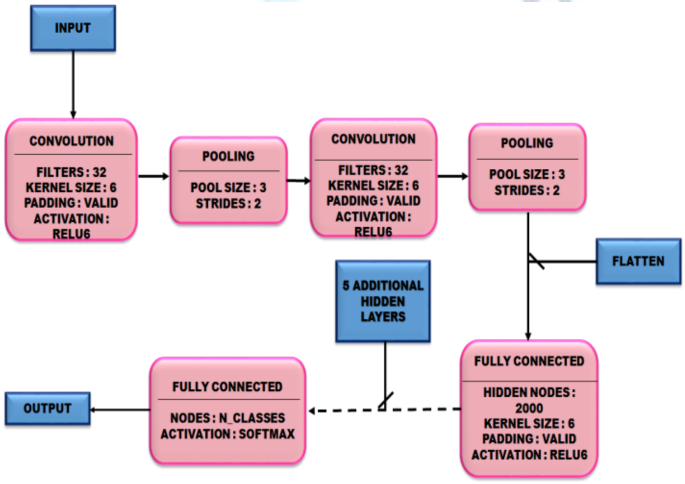

Figure 6 CNN classifier flow diagram

The filters are tiny number matrix that have input territories magnified by them. The middle of the filter is centered on each pixel in the input layer, and the filter is amplified by a province of input that is the same size as the filter. All pixels are subjected to this procedure again, with the exception of those with insufficiently large neighborhoods, and a slightly smaller initiation map is the result. Convolution results from repeatedly trying to apply the filter to the image, which can be thought of as the filter sliding over the image. A filter always raises the level of the original data.

3. RESULTS AND DISCUSSION

The proposed system implemented in MATLAB platform to verify its performance. Figure 7 (a) & (b) indicates the input image (Normal image) and cyclone image

Figure 7(a) Input image (Normal image) (b) Cyclone image

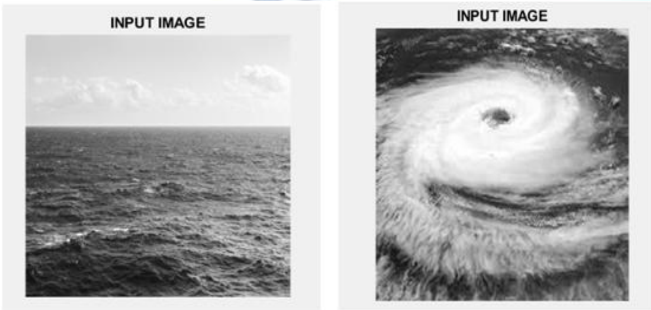

Figure 8(a) Gray Scale image for normal image and (b) cyclone image

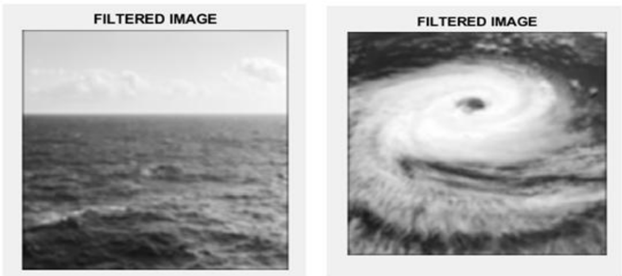

Figure 9(a) Noise reduced normal image and(b) cyclone image

The Figure 8 denotes the Gray scale image for normal and cyclone. Similarly, the Figure 9 indicates the noise reduced for normal and cyclone image.

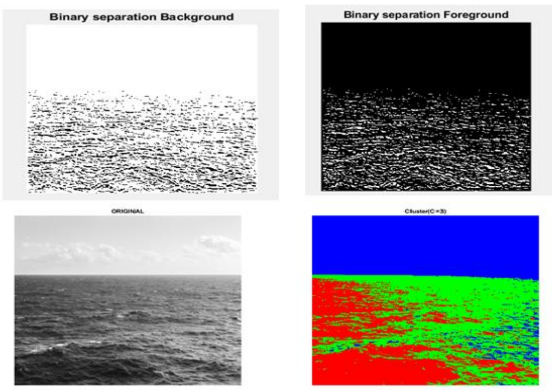

Figure 10(a)Segmentation step output images for normal data

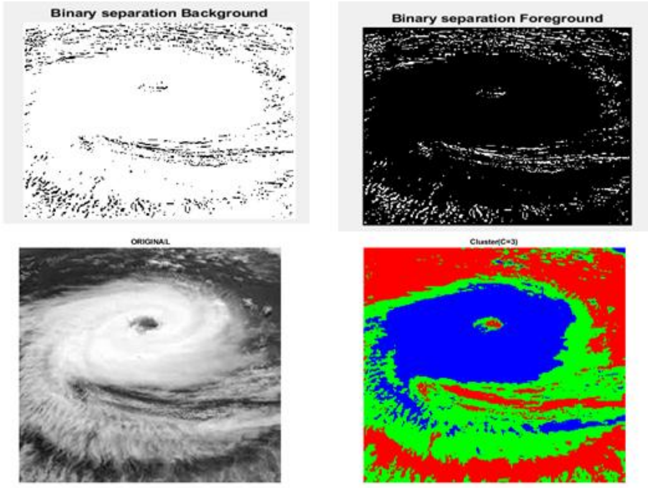

Figure 10 (b)Segmentation step output images for normal data

Figure 10 represents that segmentation step output images for normal and abnormal data. Likewise, the Figure 11 indicates the GLCM outcomes for both normal and abnormal data.

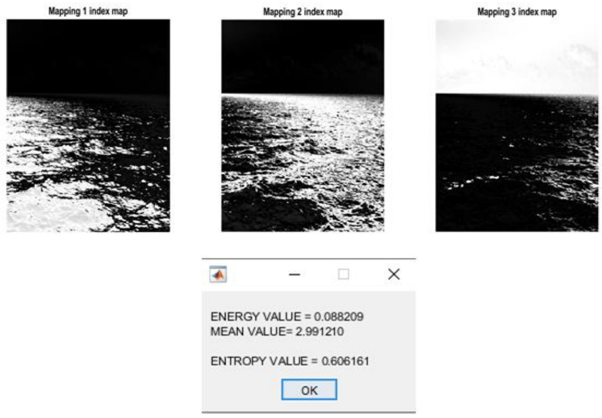

Figure 11 (a)GLCM results for normal data

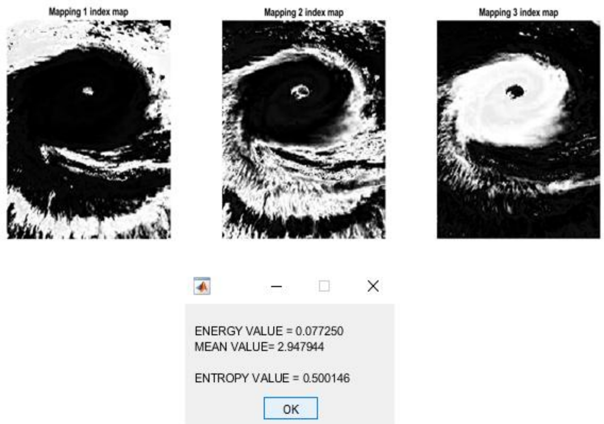

Figure 11 (b)GLCM results for abnormal data

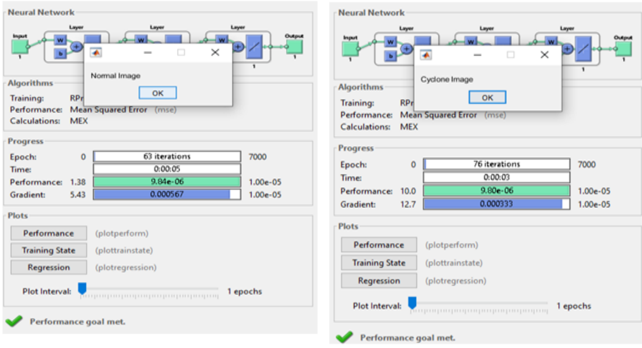

Figure 12 (a)& (b) Classification results for image 1&2

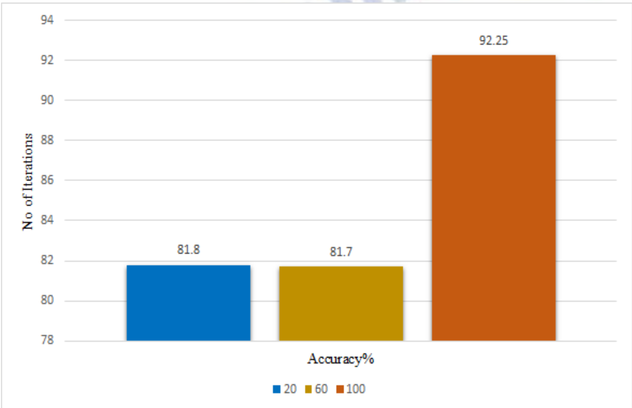

Figure 13 Performance parameters of Accuracy

Figure 12 represents the proposed classification outcomes for normal and cyclone image. Figure 13 illustrates suggested system obtained high accuracy compared to other approaches.

5. CONCLUSION

Tropical cyclones are a common natural disaster that occurs in India every year. According to statistics, three cyclones struck India's east coast in the Bay of Bengal, causing damage to human lives, crops, and property. It is critical to forecast cyclones in advance in order to avoid and mitigate massive damage. The techniques used are based on numerical models, which necessitate extensive expertise and higher skill sets in order to achieve higher prediction accuracy.As a result, the goal of this paper is to propose an effective (CSO-CDNN) model for predicting cyclones. The input image is resized and preprocessed using the Adaptive median filter. The processed image is fed into (FCM) for segmentation, and the features from the segmented output are extracted using (GLCM). The CSO-CDNN is employed to select features from the GLCM output in order to improve classification precision. When contrasted with other traditional approaches, the proposed classifier achieves the highest accuracy rate. To verify its effectiveness, the proposed CSO-CDNN classifier is implemented in the MATLAB platform.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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