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RESEARCH ARTICLE

Tropical Cyclone Intensity and Track Prediction in the Bay of Bengal Using LSTM-CSO Method

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ABSTRACT Tropical cyclones (TC) are extreme weather conditions caused by severe circular storms that originate in warm oceans. They are strong destructive forces that cause disastrous effects on human life and property and lead to economic damage. Therefore, it is necessary to forecast the TC intensity to avoid the issues. This study proposes a TC intensity forecast using Long-Short Term Memory (LSTM) with Cat Swarm Optimization (CSO). The LSTM method was optimized using the Cat Swarm Optimization technique to improve accuracy and reduce prediction errors. In this study, the prediction was carried out using the latitude, longitude, pressure, and wind speed of tropical cyclones from 2003 to 2019 in the Bay of Bengal. The performance of the proposed system was evaluated using the performance metrics, such as accuracy, Root Mean Square Error (RMSE), Average Absolute Position Error, Mean Absolute Error (MAE), and Area Under Receiver Operating Characteristic Curve (AUROC). The performance of the proposed system is compared with the results of other traditional methods, and the results show that the LSTM-CSO method outperforms other methods in TC intensity and track prediction.

INDEX TERMS Tropical cyclone, hyper-parameter tuning, cat swarm optimization, long-short term memory, pressure, wind speed.

I. INTRODUCTION

Tropical Cyclones are always a challenging concern for meteorologists, and it is necessary to forecast them employing studies such as axisymmetric structure, various forecasting techniques, and dynamic mechanisms. Tropical cyclones increase in intensity and can grow as tropical depressions, typhoons, strong typhoons, super strong typhoons, Tropical storms, and strong tropical storms. These TCs mainly occur in tropical and subtropical oceans and have a wider impact on our surroundings and environmental systems. Various factors, such as surface temperature, the thermodynamic state of the atmosphere, and the heat exchange between the ocean and TCs [1]. Other synoptic variables influencing the TC intensity are humidity, vertical wind shear, water vapour, divergence, and climatological factors. Some persistent variables that affect TC are longitude, latitude, sea-land ratio, and Julian day [2]. The Indian coastal regions are affected more frequently by tropical cyclones in the Arabian Sea and the Bay of Bengal. These basins are part of the North Indian Ocean, where the frequency of cyclones is high, and it is crucial to design a model which can forecast the TCs intensity for a longer period by analyzing for a smaller period [19].

Many numerical and statistical methods have been developed for predicting TC intensity. TC prediction techniques mostly use a dynamic model, which depends on numerical simulation and shows superior performance compared to other methods. The achievements in TC prediction were made possible by the development of supercomputers [3]. However, these dynamic models include numerical methods, which consume more time for forecasting TC. Earlier prediction allows us to take effective measures for safety and carry out rescue missions. To improve prediction, scientists considered the concept of machine learning (ML) for predicting TC. Compared to numerical simulations, ML methods process non-linear patterns and complex relationships with lower

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computational costs [4]. As the meteorological satellites, ground stations, and ocean observation stations increase, data availability also increases, leading to the problem of big data. This problem is solved using Deep Learning (DL) techniques as they can successfully handle image processing, object detection, and natural language processing [5]. Deep Learning can extract implicit features of a dataset with several variables and also elevates generalization capacity, and it has the efficiency to process huge volumes of datasets.

This study uses the Long-Short Term Memory (LSTM) method to predict tropical cyclone intensity. Using LSTM, it is possible to use various weather characteristics for a particular number of continuous time points to forecast cyclone intensity. Maximum Sustained Surface Wind Speed (MSWS) can be used as a continuous variable for intensity prediction apart from the cyclone's latitude, longitude, and pressure [19]. MSWS measures the intensity of tropical cyclones. This article implements the data from IBTrACS, which defines MSWS as the highest surface winds, and it is indicated as a 10 min average wind speed at a height of 10m above the ground level. MSWS is measured in knots, and 1 knot equals 0.514 m/s [35]. The Cat Swarm Optimization algorithm (CSO) is used for optimization. This process of hyper-parameter tuning using CSO improves the prediction results. CSO is based on a swarm intelligence algorithm originally invented by Chu and Tsai [20], [21]. The basic concept of CSO is derived from the behaviour of cats and can be implemented to solve optimization problems in the various fields of science and engineering.

A. PROBLEM STATEMENT

Prediction of TCs intensity and tracking has been made over the past decades, and many research works have been done using various algorithms and architectures, which still face challenges. Many research articles use traditional methods that do not implicitly analyze the data features and depend on the rules summarized by the historical data. Studies implement the LSTM model to predict wind speed, but very few use it for predicting the intensity of TC. The prediction of TC is influenced by the parameters such as pressure, size, and structure of the storm. The accuracy of prediction falls due to the lack of the number of observations and their quality. Overfitting, time complexity, memory, and bandwidth limitations are some problems in traditional machine-learning methods. Predicting the anomalous motions of the cyclone and making it a long-term track for forecasting is challenging. Even though evolutionary algorithms such as the classification and Regression tree algorithms are used to study the forecasting of the change in the TC intensity, Rapid Intensification (RI) process during the TC development makes forecasting challenging [22].

B. CONTRIBUTIONS

The following are the main contribution of this paper:

i. To forecast the track and intensity of TC in the Bay of Bengal (BoB) using the meteorological data with the parameters latitude, longitude, wind speed, and the pressure of the cyclones for the years 2003 to 2019.

ii. A Long-Short Term Memory (LSTM) model is implemented to predict the values based on the previous history. This model forecasts TC intensity based on the values of past hours and explores various geophysical characteristics connected with the rapid intensification of TC.

iii. The Cat Swarm Optimization technique is used to optimize LSTM to get the optimal parameters. These hyperparameters are used to improve prediction accuracy in forecasting the intensity and tracking of TC.

iv. The performance of the proposed method is evaluated using the performance metrics such as prediction accuracy, RMSE, MAE, and MAPE.

The outline of the remaining sections of this paper is as follows: Section II gives a detailed review of the previous studies done in this area. Section III describes the methodology and data set used for this article. The various effects of the meteorological data on the TC track predictions are briefly listed in Section IV. Section V displays the results, evaluation of our method, and comparisons of our method with that of others. Section 6 says the conclusion.

II. RELATED WORK

Many research works have been done using various methodologies reviewed in this paper. In earlier days, many researchers used Statistical-dynamical models to predict TC intensity which outperforms the prediction of physics-based models. Jarvinen and Neumann [6] predict the changes in TC intensity over the North Atlantic Basin over the upcoming 72h by their proposed method called Statistical regression equation (Statistical Hurricane Intensity Forecast, SHIFOR). They used predictors that were derived from persistent and climatic variables for prediction. In another work by DeMaria and Kaplan [7], A Statistical Hurricane Intensity Prediction Scheme (SHIPS) was proposed for the prediction of TC intensity changes over the Atlantic Ocean Basin. Wang et al. [8] did work in typhoon intensity forecasting by implementing a prediction model related to Feed-forward Neural Networks (FNN). They executed it for typhoon Nakri in 2014 and typhoon Molave in 2015, which yielded better results using minimum pressure and maximum wind speed that occurs in the typhoon's center. Kim et al. [9] also used FNNs and various prediction factors to predict the typhoons that cause storm surges. Shao et al. [10] implemented the forecasting model based on FNN using prediction factors chosen by multivariate stepwise regression (MSR) analysis to forecast typhoon tracks. The prediction of precipitation occurring due to typhoons is made by Huang et al. [11]. They integrated neural networks and Locally Linear Embedding (LLE) for the prediction process. Liao et al. [12] used LSTM based prediction model to predict the wind speed using the following methods: the attention mechanism, variation mode decomposition method, and wavelet decomposition method. This prediction method exhibits stability with cumulative errors. Wei and Xu [13] proposed LSTM to predict wind speed and achieve a higher accuracy rate. Geetha and Nasira [14] presented a Statistical Time Series Modeler (TSM) to predict cyclonic storms in India. They applied the TSM of SPSS (Statistical Package for Social Studies) for training and testing. The model is built on the ARIMA (Auto Regressive Integrated Moving Average) model of TSM in SPSS 20.0. A novel fusion tropical cyclone track prediction method proposed by Lian et al. [5] was based on Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU) models. Their model consists of three layers: the first layer consists of a multidimensional feature selection, and the second layer processes the selected meteorological variables in the correlated time range. Finally, in the third layer, a GRU-based model receives the extracted features from the second layer in the form of time series, and the temporal features are learned. Rüttgers et al. [4] performed a study and developed a Generative Adversarial Network (GAN) to predict the intensity and track of TC in the North-Western Pacific Ocean. They used different combinations of observational and meteorological data as input and investigated them to determine the physical parameters influencing the prediction reliability. With these combinations, 6h and 12h predictions of intensity and tracks of typhoons are conducted. An LSTM model-based typhoon prediction method was proposed by Gao et al. [15], and they trained the model using a typhoon dataset for the years 1949-2012. This method can predict 6h to 24h of typhoon tracks. Pradhan et al. [16] proposed a deep convolutional neural network architecture for clustering hurricanes depending on their intensity using a graphics processing unit. Their method shows better accuracy with the lowest RMSE. Wu et al. [17] proposed a multitask machine learning framework for forecasting the tropical cyclone intensity and its path using two modules. One module is called the prediction module; the other is the estimate module. An improved generative adversarial network is the prediction module for predicting tropical cyclones. Two deep neural networks are used as the estimation module to get the intensity and position of the generated prediction data. Varalakshmi et al. [18] proposed a TC prediction model using CNN. The optimization of the hyperparameters is done using genetic algorithms, and then it is modified by replacing the fully connected layers with conventional machine learning classifiers.

III. METHODOLOGY AND DATA

As stated earlier, our proposed method uses the LSTM tuned with the CSO technique to predict the TC track and its intensity. Fig.1 displays the workflow of our proposed method. The LSTM method forecasts TC intensity based on time series problems with the help of historical TC data. The TC prediction model is trained and tested with the processed data from 2003 to 2019 to extract the optimal prediction parameters. Then, these parameters are optimized using Cat Swarm Optimization (CSO) technique to extract the hyperparameters. These optimized hyperparameters are used for TC track and intensity prediction, showing improved accuracy and lower prediction error rates. Finally, our model's performance is evaluated with various performance metrics, and the comparison results of our method with other traditional methods are displayed.

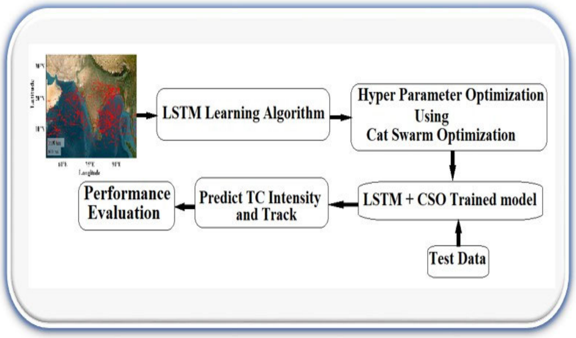

FIGURE 1. Work flow of the proposed method.

A. SCOPE OF THE STUDY AND DATA

In this experiment, tropical cyclones that occurred in the Bay of Bengal for the years 2003 - 2019 were studied. The data for our experiment is acquired from IBTrACS (International Best Track Archive for Climate Stewardship - https://www.ncei.noaa.gov/products/international-best-track-archive). The data includes the date and time of the cyclone, latitude, and longitude information, wind speed and pressure as per the World Meteorological Organization, and distance to land and landfall. This study uses the variables latitude, longitude, wind speed, and pressure for the prediction process. Sample data can be seen in Table 1; the cyclone track for 2003 to 2019 is displayed in Fig 2.

TABLE 1. Sample data of cyclone tracks from IBTrACS.

SID	SEASO	NUMBE	BASIN	SUBBAS	NAME	ISO_TIN	NATUR	LAT	LON	WMO_	WMO_	WMO_	TRACK_
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.5	85.1				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.51686	84.9668				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.53697	84.837				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.5636	84.7136				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.6	84.6				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.64755	84.4976				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.7	84.4				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.75	84.3075				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.8	84.2				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.835	84.05				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	3.9	83.9				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	4.02	83.7925				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	4.2	83.7				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	4.435	83.5925				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	4.7	83.5				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	4.965	83.4425				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	5.2	83.4				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	5.365	83.35				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	5.5	83.3				main
2005007N	2005	3	NI	BB	NOT_NAM	#########	TS	5.65	83.2425				main

The pressure and wind speed also influence Tropical Cyclones. The cyclones' pressure, wind speed, and cyclone tracks from 2003 to 2019 are shown in Figure 2 (A) and (B) and (C), respectively.

The changes in the pressure and wind speed over time are shown in Figure 3 (A) and (B), respectively, period of five years (2005 to 2010)

B. METHODOLOGY

1) LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory is one of the complex areas in Deep Learning, which deals with the algorithms that mimic

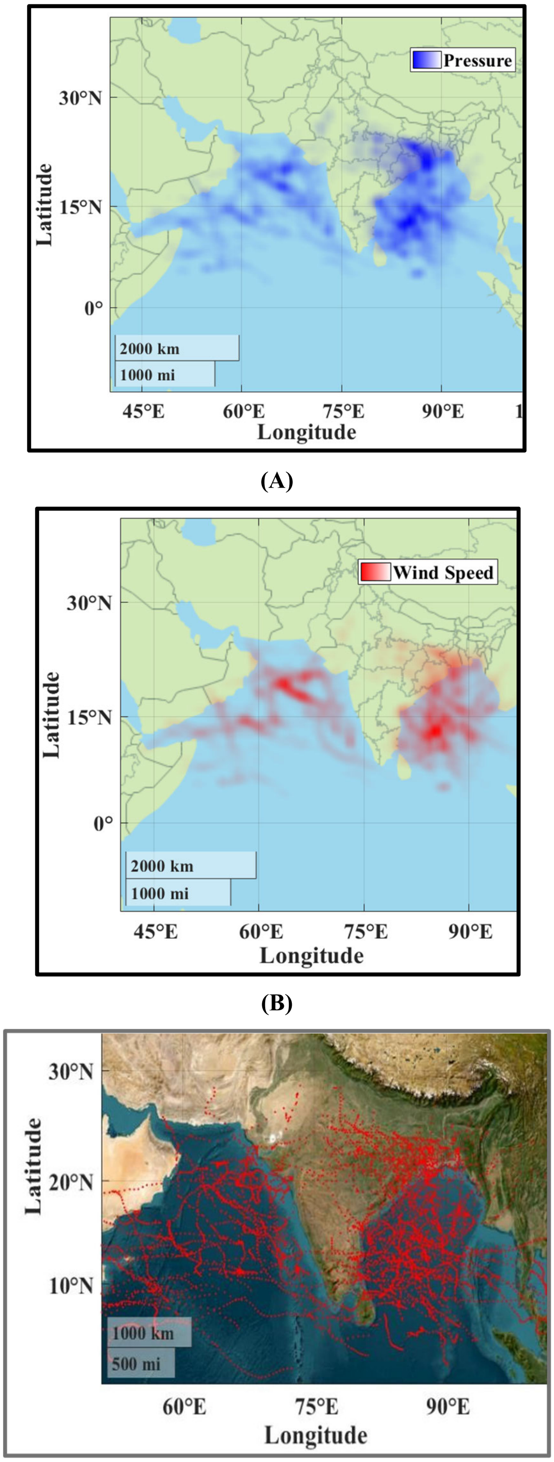

FIGURE 2. **(A) Pressure, (B) Wind speed, and (C) Cyclone tracks from 2003 to 2019.**

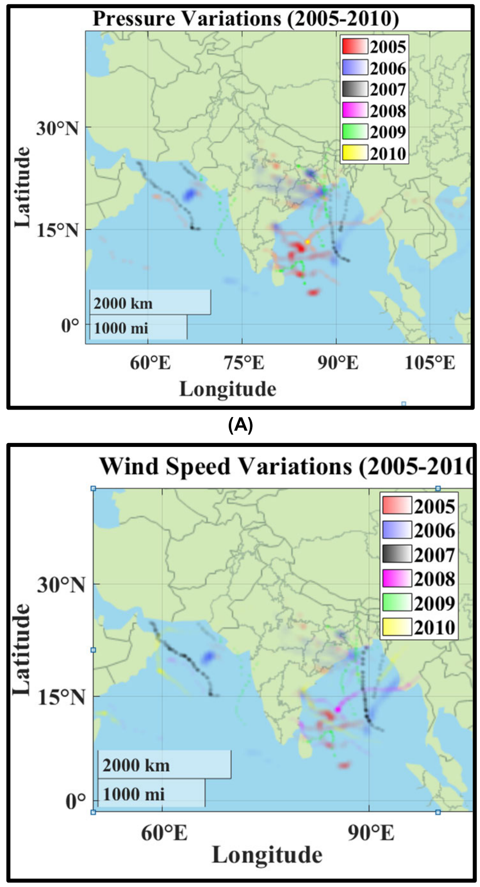

FIGURE 3. **Figure 3(A) shows the changes in pressure and 3(B) wind speed over a period of 5 years (2005 to 2010).**

the brain of humans. It is an improved version of the Recurrent Neural Network (RNN). RNNs get a sequence of inputs to produce outputs influenced by weights and the hidden state vector, representing the learned information based on previous inputs and outputs. The gradient vector of RNN increases or decreases exponentially during the training process, which can lead to vanishing or exploding gradient issues. That is why RNNs cannot withhold a very long-term history of the past. This issue is resolved using the Long Short-Term Memory Networks. [29]. The traditional RNN consists of one internal state denoted by $_{\mathrm{it}}$, which is computed repeatedly in each time step by the equation

$$h_t = g(W_{xt} + \mathrm{Uh}_{\mathrm{t}-1} + b) \tag{1}$$

where g indicates the activation function, W and U are the weight matrices of the hidden state h, which are adjustable, and x b is the adjustable input bias vector. Initialization of the hidden state is done at the first time step as a vector of zero, and the length of the vector is a user-defined parameter.

As mentioned earlier, the vanishing and exploding gradients are prevented by using a Constant Error Carousel (CEC), which maintains an error signal inside each unit's cell. These cells are not RNNs but are loaded with additional features called the input and output gates and form the memory cell. In this LSTM model, the hidden units are replaced by the memory cells containing the input, output, and forget gates. During implementation, the information regarding the latitude, longitude, pressure, and wind speed is given as input parameters to the input gate, with an initial interval of 6h. The process is repeated to find the cyclone track for 12h, 36h, and 48h. These gates control the internal operations of the network. Apart from the memory gates, the basic components of the LSTM model consist of the cell state c_t, which stores the information, the tanh activation function, and the sigmoid. The gates control the addition and deletion of information to and from the cell states. The sigmoid activation function in the gates is used to multiply the input and identifies the data to include or remove [27]. Each LSTM unit maintains an Internal Cell State vector c_t which describes the information that has to be included by the previous LSTM unit. The LSTM network comprises three gates: (i) Forget gate, (f), (ii) Input gate, and the (iii) Output gate. The forget gate (f) determines the degree of the previous data (previous cell state $c_{t-1)}$ to be forgotten,

$$f_t = \sigma(\mathrm{W_f X_t} + \mathrm{U_f h_{t-1}} + b_f) \tag{2}$$

Next, an update vector is computed for the cell state using the current input (tx) and the last hidden state (h_{t-1}), given by equation 3.

$$\tilde{c_t} = \tanh(\mathrm{W}_{\tilde{c}}\mathrm{x_t} + \mathrm{U}_{\tilde{c}}\mathrm{h_{t-1}} + b_{\tilde{c}}) \tag{3}$$

The above equation $\tilde{c_t}$ indicates the vector with the values between $(-1,1)$, tanh denotes the hyperbolic tangent, and W_c, $U_{c,}$ and B_c are the learnable parameters. The second gate is the input gate that defines which and up to what extent the information should be included in the Internal Cell State in the current time stamp, which is given by the equation,

$$i_t = \sigma(\mathrm{W_i i x_t} + \mathrm{U_i h_{t-1}} + b_i) \tag{4}$$

where i_t is the vector having the values of the range (0,1) and W_i, $U_{i,andbi}$ are the set of learnable parameters that are defined for the input gate. From equations (2) to (4), the updated cell state is given by the equation:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c_t} \tag{5}$$

where $\odot$ indicates the element-wise multiplication. The third gate is the output gate o_t, which controls the information flow in the cell state (c_t) to the new hidden state h_t. In this study, the output gate gives the next location of the cyclone track, which is calculated from the previous latitude and longitude values. The following equation computes the output gate.

$$o_t = \sigma(\mathrm{W_o x_t} + \mathrm{U_o h_{t-1}} + b_o) \tag{6}$$

where it is the vector with the values between the range (0,1) and Wo, Uo, and bo are the output-defined set of learnable parameters for the output gate. From o_t, a new hidden state is computed, and the combination of the results of the equations (5) and (6):

$$h_t = \tanh(o_t) \odot o_t \tag{7}$$

The cell state c_t is vital in effectively learning the long-term dependencies. The interactions with the LSTM cell are simple and linear; it can store information for longer steps without changing. This characteristic of the LSTM helps to overcome the issue of exploding and vanishing gradients during the training process. Like neural networks, which consist of multiple neurons in one layer, LSTM, too, can choose the length of the cell and the number of hidden state vectors freely and can stack n number of layers on top of one another. The output of the last LSTM layer at the time step $(h_{n)}$ is linked through a dense layer into a single output neuron that computes the final prediction by equation 8. The final output in the proposed method is the final predicted track.

$$y = \mathrm{W_d h_n} + b_d \tag{8}$$

Here, y is the final output, h_n is the output yielded from the last LSTM layer at the last time step, W_d denotes the weight matrix of the dense layer, and b_d denotes the bias term.

2) THE CAT SWARM OPTIMIZATION (CSO) ALGORITHM

The proposed method uses the Cat Swarm Optimization algorithm (CSO) for the hyper-parameter tuning. The parameters used in the LSTM are optimized using CSO for better prediction. In this study, the values of the latitude and longitude positions of the track are predicted. These parameters are tuned using the CSO algorithm. CSO was originally a continuous and single objective one, and it has been inspired by the two behaviour of cats resting and tracing [20]. While resting, the consciousness of the cats is high and was aware of the happenings surrounding them as they constantly observe them intelligently. As they find a target, they move quickly toward it. The CSO algorithm is based on the two behaviours of cats: seek and trace modes. Each cat denotes a set of solutions with its position, a flag, and a fitness value. The positions consist of M dimensions of the search space, and every dimension has its velocity. The fitness value indicates how good the solution set is, and finally, the flag classifies the cats into seek or trace mode [33]. The algorithm should specify the number of cats engaged for the iteration. The best cat is chosen and saved in memory in each iteration, and the cat at the final iteration gives the solution. Concerning the study, for each iteration, the next best location of the track is saved, and the final iteration gives the entire predicted track of the cyclone.

a: SEEKING MODE

This mode simulates the resting behaviour of the cat. Four basic parameters play vital roles. They are Seeking Memory Pool (SMP), Seeking a range of the selected dimension (SRD), Counts of Dimension to Change (CDC), and last, Self Position Considering (SPC) [21]. The user defines and tunes these values using the trial and error method. The workflow of the seek mode is as follows:

Step 1: Make many SMP copies for the current position of Catk.

Step 2: Randomly select CDC dimensions to be mutated, and from the current value, randomly add or subtract SRD values and replace the old ones as shown in the equation below:

$$Xjd_{new} = (1 + rand * SRD)Xjd_{old} \tag{9}$$

where Xjd_{old} is the current position, and Xjd_{new} denotes the next position. j is the number of the cat, d is the dimension, and the interval of the random number is between [0,1].

Step 3: Find the fitness value for all the candidate positions.

Step 4: Depending upon the probability, choose one of the candidate points as the next position of the cat for which the candidate points with higher fitness value have more chance to get selected, as shown in equation (9). Suppose all of the fitness values are the same; then, the probability of each candidate is 1.

Step 5: If the fitness function aims to find the minimum solution, choose $F_{Sb} = FS_{max}$, or $FS_b = FS_{min}$ for the other case.

b: TRACING MODE

This mode imitates the tracing behaviour. The random velocity values are assigned to all dimensions of the cat's position. The upcoming steps update the velocity values.

Step 1: Update the velocities ($V_{k,d}$) for all the dimensions as specified in equation (10).

Step 2: If a velocity value exceeds the maximum value, set it as the maximum.

$$V_{k,d} = V_{k,d} + r_1 c_1 (X_{best,d} - X_{k,d}) \tag{10}$$

Step 3: Update the position of Catk as per the following equation:

$$X_{k,d} = X_{k,d} + V_{k,d} \tag{11}$$

Xbest,d is the position of the cat with the best fitness value, Xk,d is the position of the Catk, c1 is a constant, and r1 is a random number in the range between [0,1]. Algorithm 1 shows the overall process of the CSO algorithm.

Algorithm 1 Pseudocode of the CSO Algorithm

Step 1: Initialize the population of cats.
Step 2: Randomly locate the cats in the solution space and assign the values for position and velocity for each cat.
Step 3: Pick the cats in Trace Mode in a haphazard way and assign other cats in the Seeking Mode
Step 4: Evaluate the fitness values of cats in the population, select the best cat, and store it in X_{best}.
Step 5: Concerning the modes of the cats, move Cat_k them to the SM process. Move them to the Tracking Mode process if it is in seeking mode or otherwise.
Step 6. Re-pick the population of cats and divide them into SM or TM again
Step 7: If the termination condition is reached, stop the process and return the Best cat (X_{best}) value as it has the best solution. Otherwise, repeat steps 3 through 5.

IV. RESULTS AND DISCUSSIONS

The proposed LSTM-CSO model is compared with other tropical cyclone track prediction methods for performance evaluation. In order to evaluate the efficiency of the proposed method, the same is applied to other oceans and basins for the same period of time (2003 to 20019), and the proposed method achieves higher accuracy. The performance comparison metrics accuracy, precision F1 score, and recall values of the models LeNet, AlexNet, and VGG-16 [1] are compared with the proposed model, and the results are displayed in Fig 3 (a). The graph shows that our proposed method performs better than the traditional methods. The proposed method's performance increase due to tuning the hyperparameters MaxEpochs, Gradient Threshold, and initial learning rate of the LSTM model with the implementation of the CSO algorithm.

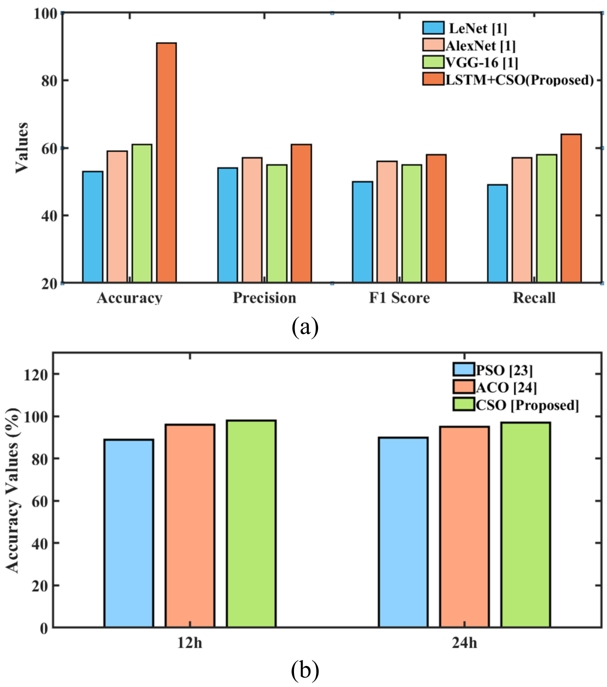

FIGURE 4. (a) Comparison of the proposed method with other traditional methods based on various performance metrics (b) Comparison of optimization algorithms based on 12h and 24h prediction accuracy using hyper-parameter tuning.

A comparison of hyperparameter tuning using the CSO algorithm is also made with other optimization algorithms, such as Particle Swarm Optimization (PSO) [23] and Ant Colony Optimization (ACO) algorithms. The performance evaluation is done based on accuracy in prediction for 12h and 24h lead time, and the CSO algorithm gives better accuracy in prediction, as shown in Fig 3 (b). In order to show the efficiency of our proposed method, the RMSE (in knots) values for 12h and 24h lead time of the proposed method are compared with the results of the Neural Network (NN) model [24], Multilayer Feed Forward Neural Network (MFFNN) model [26] and the results of the Indian Meteorological Department (IMD) [25].

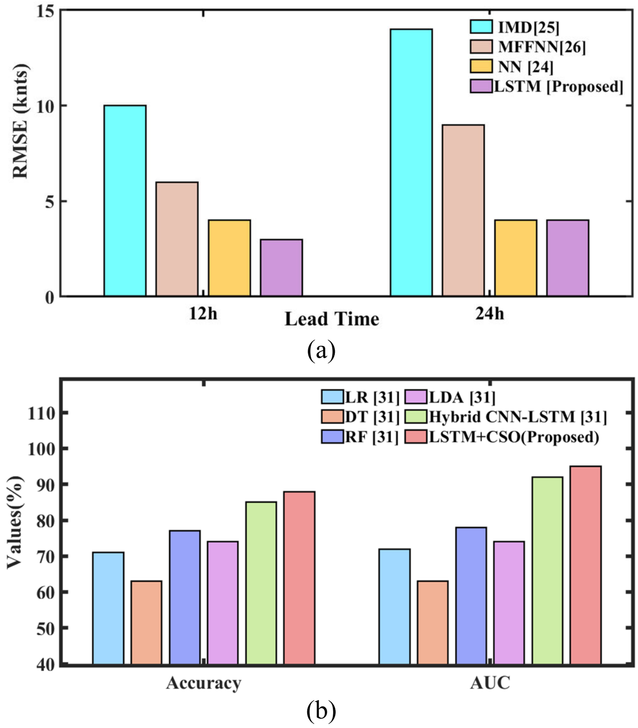

FIGURE 5. (a) Comparison of RMSE (knits) values with other models. (b) Accuracy and AUC comparison with other deep Learning methods.

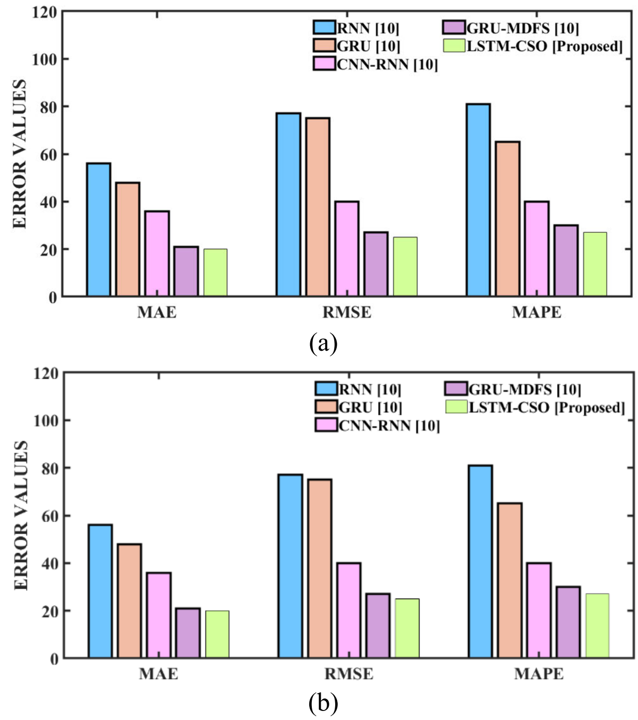

FIGURE 6. Performance comparison of MAE, RMSE, and MAPE of other traditional methods with the proposed method during prediction in (a) Latitude (b) Longitude.

TABLE 2. Comparison of other optimization methods with the proposed method in three areas.

	Accuracy (%)		
Methods	Arabian Sea	Indian Ocean	Bay Of Bengal
ACO	94.6	95.3	95.8
PSO	98	97.7	98.9
LSTM+CSO	98.9	99.2	99.4

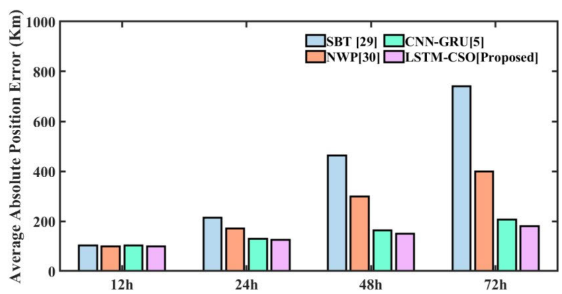

FIGURE 7. Performance Comparison of the proposed method with other methods by evaluating the average absolute position error for 12h, 24h, 48h, and 72h of prediction.

The RMSE values are considerably reduced with the proposed LSTM-CSO method, as depicted in Fig 4(a). The prediction accuracy and the AUC (Area Under the ROC) values are compared with the traditional DL methods like Linear Regression (LR), Decision Trees (DT), Random Forest (RF), Linear Discriminant Analysis (LDA), and Hybrid CNN-LSTM method [31] and the proposed method outperforms other methods in both the cases as shown in Fig 4 (b).

The performance evaluation of the proposed method is done with other traditional methods [10], such as Recurrent Neural Networks (RNN), Gated Recurrent Unit (GRU), CNN-RNN, and GRU with Multidimensional Feature Selection (MDFS) by comparing the errors in prediction using the metrics Mean Absolute Error (MAE), RMSE, and Mean Absolute Percentage Error (MAPE). The prediction results are shown in Fig 5 (a) for latitude and in Fig 5 (b) for longitude, in which the LSTM-CSO method shows better performance with the latitude and longitude prediction almost close to the observed values. The CNN model performance is not remarkable as there is no way to extract the temporal features. Finally, our method outperformed other methods in predicting the TC for 12h, 24h, 48h, and 72h lead time with lower Average Absolute Position Error (Km) when compared with methods such as the Sanders Barotropic technique (SBT) [29], Numerical Weather Forecasting (NWP) [30] and CNN-GRU with multidimensional Feature model [5] and the results are displayed in Fig 6.

Some of the images of Tropical cyclones that occurred from 2003 to 2019 are displayed in the following figure (Fig 7). The images in Fig 7 (a) are taken from

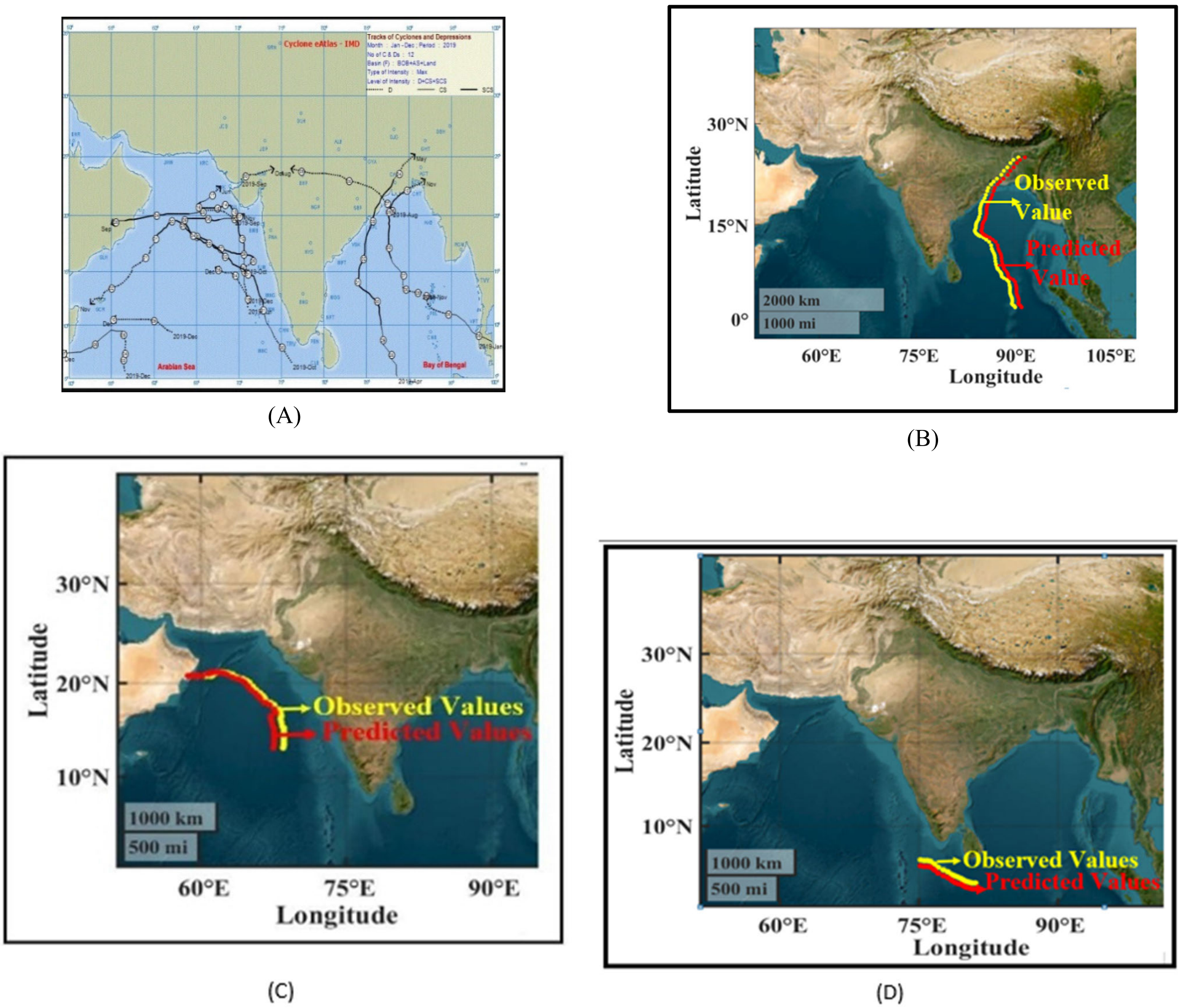

FIGURE 8. Fig (a) shows the Tropical Cyclone tracks in the Bay of Bengal in 2019. The observed and predicted tracks of the TC using the proposed LSTM-CSO method: (b) in the year 2019 in the Bay Of Bengal, (c) in the year 2015 in the Arabian Sea, and (d) in the year 2018 in the Indian Ocean.

TABLE 3. Performance evaluation of our method with other traditional methods.

Method	HR	FAR	PSS
LDA [29]	0.78	0.13	0.64
DT [29]	0.93	0.28	0.65
RF [29]	0.95	0.25	0.7
SVM [29]	0.90	0.2	0.71
LSTM [Proposed]	0.97	0.2	0.79

https://rsmcnewdelhi.imd.gov.in/report.php?internal_menu=MzM=, which shows the cyclone tracks in the Bay of Bengal for the year 2019.

To represent the prediction of the proposed model, a cyclone track from 2019 is visualized in Fig 7 (b). The results are obtained by implementing the previous 12h data for prediction. The yellow dots indicate the original TC track, and the red dots represent the predicted track. The following table (Table 2) compares other optimization techniques with the proposed method. We tested the ACO and PSO algorithms for the cyclone tracks of the Arabian Sea and the Indian Ocean, and the results are compared based on accuracy in prediction. Our proposed LSTM-CSO method performs better in all three cases with higher accuracy.

The evaluation of the proposed method's performance is carried out by comparing the values of Hit Rate (HR), False Alarm Rate (FAR), and Pierce Skill Score (PSS) of four different DL methods [28] for predicting TC. Table 3 lists the comparison results, and the values clearly show that the LSTM-CSO method performs better than other models. The other methods used satellite data for TC prediction.

TABLE 4. Performance evaluation of the proposed method with (Gradient Boost Regression Tree Model) GBRT regarding R^2, MAE, and RMSE.

Predict Time	R^2		MAE (m/s)		RMSE(m/s)	
	GBRT [2]	LSTM+ CSO (Proposed)	GBRT	LSTM+ CSO	GBRT	LSTM+ CSO
12h	0.6	0.7	2	2	3	3
24h	0.7	0.74	4	3	5	4
36h	0.75	0.81	5	4	7	7
48h	0.75	0.83	6	5	9	8
60h	0.78	0.86	7	5	10	9
72h	0.79	0.89	8	7	11	9

The forecast for 12h, 24h, 36h, 48h, 60h, and 72h prediction results of the Gradient Boost Regression Tree Model [2] are compared with the proposed LSTM-CSO model based on R^2, MAE, and RMSE values and the results are shown in Table 4.

V. CONCLUSION

This paper proposes an LSTM-CSO-based prediction model for predicting Tropical Cyclones in the Bay of Bengal region from 2003 to 2019. The data for the model is taken from IBTrACS, which consists of the tracks' latitude, longitude, pressure, and wind speed. The prediction is made using the LSTM model, which can withhold the long-term history of the past information without vanishing or exploding gradient problems. The prediction uses some years' track data for validation and others for testing. This Long Short Term Memory model predicts cyclones more accurately when compared to other traditional models with lower forecast error rates. The proposed method uses the Cat Swarm Optimization algorithm for hyperparameter tuning, which performs better than other optimization methods such as PSO and ACO algorithms. The performance comparison of these optimization techniques is carried out, and the results show that the CSO technique performs better than the other two algorithms. Performance evaluation of our methods is done by comparing various methods using different metrics, and the results are displayed in the previous section.

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