Discrete Migratory Bird Optimizer with Deep Learning Driven Cyclone Intensity Prediction on Remote Sensing Images

S. Jayasree
Department of Computer Science, SRM Institute of Science and Technology, Vadapalani Campus, India
subrad1997@gmail.com (corresponding author)

K. R. Ananthapadmanaban
Department of Computer Science, SRM Institute of Science and Technology, Vadapalani Campus, India
kranantp@srmist.edu.in

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ABSTRACT

Tropical Cyclones (TCs) are extreme climatic conditions that can crucially disrupt human life. Heavy rainfall and resilient winds that follow these systems can result in severe consequences for property and hamper social and economic growth in respective areas. Thus, accurate assessments of TC intensity is paramount for practical applications and theoretical research in predicting and preventing disasters. Satellite Cloud Images (SCIs) are a primary preferable and effective data source for the study of TCs. Efficient and accurate estimation of TC intensity is often challenging despite the remarkable success in different SCI-based studies. Recently, Machine Learning (ML) and Deep Learning (DL) methods have shown significant potential and gained fast development against big data, especially with images. Considerable progress has been made in applying Convolutional Neural Networks (CNNs) to predict and evaluate the intensity of TCs. This study focuses on developing a Discrete Migratory Bird Optimizer with Deep Learning Dirven Cyclone Intensity Prediction (DMBODL-CIP) technique on remote sensing images to estimate the intensity levels of TCs. To accomplish this, the DMBODL-CIP technique initially undergoes preprocessing in two phases: Bilateral Filtering (BF) and Adaptive Histogram Equalization (AHE)-based noise removal and contrast enhancement. The DMBODL-CIP technique utilizes a deep CNN-based SqueezeNet model for the feature extraction process. Then, a Deep Belief Network (DBN) model is used to predict TC intensity. Finally, the DMBO technique is employed for optimal hyperparameter selection of the DBN model, which assists in improving the overall prediction results. The proposed DMBODL-CIP approach was evaluated on a cyclone image dataset and a comparison study showed an RMSE of 6.02 kt outperforming existing techniques.

Keywords-tropical cyclones; remote sensing image; contrast enhancement; discrete migratory bird optimizer; deep learning

I. INTRODUCTION

TCs are extremely critical natural disasters, and their precise evaluation can be crucial to avoiding and minimizing damage [1]. Intensity is an important component of TC parameters, as it depends not only on several features, namely environmental conditions, inner TC structures, and their relations, but it differs unpredictably with time and location [2]. Consequently, research on TC intensity is a primary concern in oceanography and meteorology, as due to the large scale of TC structures and the problematic development in the spatial-temporal domain, the description of TC intensity through earth-based equipment is difficult [3]. Given the limitations of numerical techniques, statistical models offer greater adaptability while requiring fewer computational resources, opening new opportunities in big data analysis [4]. Conventional methods such as the Statistical Hurricane Intensity Prediction Scheme (SHIPS), standard regressions, and Generalized Additive Models (GAM) are used for TC predictions. However, traditional non-linear regression struggles to capture complex non-linear relationships [5].

Many of these models are based on experience-based manipulations, which can lead to specific errors and reduced efficiency [6]. There is a critical need for more accurate techniques to estimate the TC intensity. Recent advances in ML, specifically CNNs, have crucially improved the extraction and classification of complex TC data [7]. Although specialized Neural Networks (NNs) enhance prediction reliability, the high costs of airborne observation limit their global application. This underscores the need for innovative methods that can effectively analyze TC data in various spatial and temporal contexts [8]. Satellite remote sensing, particularly from SCIs, provides continuous data on TCs and their surrounding environments, making it a valuable resource for research and analysis. Accurate intensity prediction is essential for effective disaster management, as TCs pose significant risks [9]. Traditional observation methods often fail, especially before landfall, underscoring the need for advanced models. This research aims to improve TC intensity prediction through DL and innovative optimization models, ultimately enhancing preparedness and response strategies [10].

This study presents a novel Discrete Migratory Bird Optimizer with Deep Learning Dirven Cyclone Intensity Prediction (DMBODL-CIP) technique on RSIs. To achieve this, the DMBODL-CIP technique improves the quality of the input images via Bilateral Filtering (BF) and Adaptive Histogram Equalization (AHE)-based noise removal and contrast enhancement. Additionally, the DMBODL-CIP method utilizes the SqueezeNet method to derive feature vectors. A Deep Belief Network (DBN) classifier is employed with DMBO-based hyperparameter tuning to predict the TC intensity levels. To ensure the performance of the DMBODL-CIP technique, a simulation was performed on a cyclone image dataset. The key contributions of the DMBODL-CIP technique are as follows.

- Utilizes BF and adaptive histogram equalization to effectively eliminate noise and improve the contrast of the input images. This enhances the overall quality of the data for accurate TC intensity predictions.
- Utilizes the SqueezeNet model to extract effectual feature vectors from the processed images. This results in a lightweight model that achieves high performance for TC intensity prediction.
- Utilizes a DBN classifier to precisely predict TC intensity levels. This facilitates the effectual interpretation of the extracted features, resulting in improved prediction accuracy.
- Incorporates DMBO-based tuning to optimize the hyperparameters of the DBN classifier. This model also improves prediction performance, achieving more reliable intensity forecasts for TCs.
- Integrates advanced image processing models with a lightweight NN for feature extraction and a robust classifier. The novelty is in the incorporation of these methods to substantially enhance the prediction accuracy of TC intensity, allowing more effective disaster management.

II. LITERATURE WORKS

In [11], a physics-enhanced CNN was presented that incorporated successive IR images from satellite images and previous data of TCs, including Minimum Pressure (MP), MSW, and Center Position (CP). Multichannel images were arbitrarily separated into a specific ratio. Sensitivity experiments could be developed to examine the effect of various inputs on the effectiveness of the model. In [12], an NN model was proposed, called TC-Pred,. An innovative feature extraction and aggregation technique was developed using multiple source environmental indicators. Additionally, a technique influenced by the convolutional transformer was devised. In [13], a new TC intensity evaluation method was developed using a Deep Multisource Attention Network (DMANet). In addition, a message-passing improvement method relied on Conditional Random Fields (CRFs). Then, a local-global attention method was employed, focusing on local key features and acquiring TC deep global semantic data. Finally, a Kalman filter was utilized.

In [14], the Temporal Attention Mechanism ConvLSTM (TAM-CL) method was proposed, which improved the extraction of 3D spatiotemporal features by employing ConvLSTM with 3D convolution kernels combined with an attention mechanism. In [15], advanced deep learning and smoothing techniques were employed, using a Vision Transformer (ViT) DCNN for regression and a classification phase, along with four precise smoothing methods for both methods and their fusion. In [16], the STE-TC spatiotemporal encoding model was introduced. In [17], a TL-based TC intensity assessment technique was presented. The pre-trained method was designed by utilizing the Swin-T. Next, a TL model was presented by fine-tuning the pre-trained method. In [18], a linear support vector regressive gradient descent Jaccardized deep multilayer perceptive (LEGEMP) was introduced. The chosen features fed the Nesterov gradient descent jeopardized deep-MPC. However, models that balance complexity and interpretability are needed to allow effective real-time tropical cyclone predictions and enhance the generalizability of Transfer Learning (TL) across diverse datasets.

III. THE PROPOSED MODEL

This study developed the DMBODL-CIP technique to estimate the intensity levels of TCs using an optimal DL model. The DMBODL-CIP technique involves four different processes: preprocessing, feature extraction, DBN-based prediction, and DMBO-based hyperparameter tuning. Figure 1 presents the structure of the proposed DMBODL-CIP technique.

A. Preprocessing

Initially, the DMBODL-CIP technique performs preprocessing in two stages: BF and AHE-based noise removal and contrast enhancement [19]. BF is a complex noise removal process increasingly used in image processing and remote sensing applications. It efficiently suppresses noise while ensuring details and edges in the image. Unlike classical smooth filtering that averages pixel values within the neighborhood, the BF considers the intensity similarity and spatial proximity between pixels. Integrating the weighted average based on the pixel intensity difference and spatial distance ensures that noise is reduced without blurring essential features, making it especially applicable for RSI where preserving spatial reliability is critical for interpretation and accurate analysis. The adaptability of BF to noise features and its ability to retain image details make it a crucial preprocessing stage in increasing the utility and quality of RS data. AHE is a powerful model to improve contrast in RSIs [20]. Unlike conventional histogram equalization that applies uniform contrast adjustments, AHE dynamically alters the contrast based on local pixel neighborhoods. This adaptability efficiently compensates for variations in terrain and lighting, enhancing the visualization of both prominent and subtle details. AHE improves the analysis and interpretation of remote sensing data by delivering clearer and more informative images.

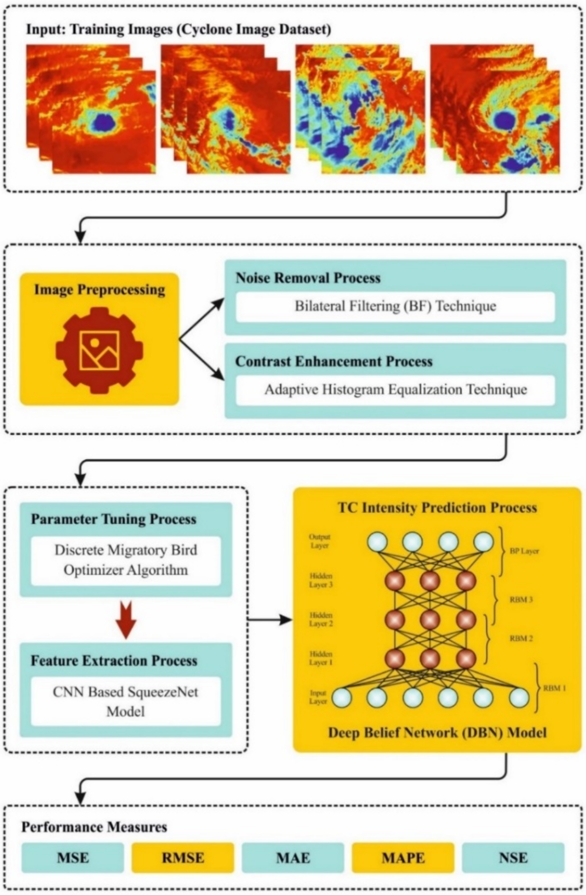

Fig. 1. Structure of the DMBODL-CIP approach.

B. Feature Extraction Process

The DMBODL-CIP technique utilizes a deep CNN-based SqueezeNet model for the feature extraction process [21]. Due to greater efficiency, CNNs are standard DL models today and are extensively employed in a wide range of uses. Like Artificial Neural Networks (ANNs), CNNs consist of neurons that use weights and biases to cover a decision-making procedure in the subsequent layer. The large Hidden Layer (HL) size in fully connected networks slows image identification. SqueezeNet, with a structure similar to AlexNet but 50 times fewer parameters, is ideal for mobile devices. It replaces traditional fully connected layers with global average pooling, generating class-specific feature maps for direct input to the Softmax layer, enhancing efficiency and performance compared to traditional CNNs.

C. TC Prediction Using the DBN

The DMBODL-CIP technique employs a DBN model, which is a probability-based generative network containing a sequence of Restricted Boltzmann Machine (RBM) and BPNN [22]. This method excels in TC prediction by capturing complex patterns in massive datasets through unsupervised pre-training, improving accuracy, and allowing real-time forecasting in dynamic environments. The DBN comprises of HLs, an output layer, and a Visible Layer (VL). The VL acts as the input layer, where features are removed to explore manifold HLs. Each RBM is trained layer-wise with unsupervised models, followed by supervised fine-tuning using labeled data to optimize DBN parameters.

1) RBM Pre-Training

There is a bi-directional link in the intermediate of the dual layers, without a relationship in the intermediate of the cell layers. Assume that the amount of components in the VL is m. The VL is signified by the vector $v = \{v_1, v_2, \ldots, v_m\}$, and at the same time, the amount of units in the HL is represented by n. The vector $h = \{h_1, h_2, \ldots, h_n\}$ signifies the HL. The RBM energy function is described by:

$$E(v, h; \theta) = -\sum_{j=1}^{m}\sum_{k=1}^{n} \omega_{jk}\, v_j h_k - \sum_{j=1}^{m} a_j\, v_j - \sum_{k=1}^{n} b_k\, h_k \quad (1)$$

where θ and b_k denote the set of RBM parameters and the HL unit deviation, ω_{jk} and a_i indicates the link weight among the HL node and input layer and the unit deviation of the VL. The mutual dispersion of the layer is calculated using an RBM:

$$p(v, h) = \frac{1}{R(\theta)} e^{-E(v,h)} \quad (2)$$

$$R(\theta) = \sum_{v,h} e^{-E(v,h)} \quad (3)$$

where $R(\theta)$ represents the factor of normalization. The independent probability dispersion of VL is given by:

$$p(v) = \sum_h p\,(v, h) = \frac{1}{R(\theta)} \sum_h e^{-E(v,h)} \quad (4)$$

Since no link occurs at the intermediate of the node, the conditional probability dispersions are:

$$p(h_k = 1|v; \theta) = \sigma\left(\sum_{j=1}^{m} \omega_{jk}\, v_j + b_k\right) \quad (5)$$

$$p\left(v_j = 1\middle|h; \theta\right) = \sigma\left(\sum_{k=1}^{n} \omega_{jk}\, h_k + b_j\right) \quad (6)$$

where $\sigma(x) = \frac{1}{1+\exp x}$ represents the activation function from the HL probability neurons intended by the VL and parameters.

RBM aims to increase the probability value $p(v)$ by altering the weights ω_{jk} and biases a_j, b_k. The set of RBM parameters $\theta = \{a_j, b_k, \omega_{jk}\}$ are obtained from the model with the highest likelihood estimate by the subsequent gradients for each parameter.

$$\frac{\partial \ln p(v)}{\partial \omega_{jk}} = \langle v_j h_k \rangle_{data} - \langle v_j h_k \rangle_{model} \quad (7)$$

$$\frac{\partial \ln p(v)}{\partial a_j} = \langle v_j \rangle_{data} - \langle v_j \rangle_{model} \quad (8)$$

$$\frac{\partial lnp(v)}{\partial b_k} = \langle h_k \rangle_{data} - \langle h_k \rangle_{model} \quad (9)$$

where $\langle \cdot \rangle_{model}$ and $\langle \cdot \rangle_{data}$ denote the probability of the rebuilt and existing RBM technique data distribution. The model of contrast scattering upgrades the factor θ.

$$\omega_{ik^{(t+\triangle t)}} = \omega_{jk}^{(t)} + \frac{\alpha}{\beta}\left(\langle v_j h_k \rangle_{data} - \langle v_j h_k \rangle_{model}\right) \quad (10)$$

$$\omega_j^{(t+\triangle t)} = \omega_j^{(t)} + \frac{\alpha}{\beta}\left(\langle v_j \rangle_{data} - \langle v_j \rangle_{model}\right) \quad (11)$$

$$\omega_k^{(t+\triangle t)} = \omega_k^{(t)} + \frac{\alpha}{\beta}\left(\langle h_k \rangle_{data} - \langle h_k \rangle_{model}\right) \quad (12)$$

where α and β refer to the learning rate and step size.

After training the RBM, the existing HL converts into the VL of the following RBM. Once every RBM is trained, depth features are removed layer-wise at the novel feature series.

2) DBN Fine-tuning

To obtain the global optimized parameters of the DBN method, every RBM layer only certifies that the weights grab the optimum feature vector mapping instead of mapping the complete DBN. So, the BP networks spread the error data to every RBM layer from upper to lowest to perfect the complete DBN method. With the RBM procedure, the DBN can overcome the defects of BP networks.

D. Hyperparameter Tuning Process

Finally, the DMBO technique is employed for the optimal hyperparameter selection of the DBN method, helping to improve the overall prediction results [23]. This method is ideal due to its effective exploration of the search space and its ability to converge quickly on optimal solutions. This model balances exploration and exploitation, enhancing ML performance while reducing computational costs. Here, leaders and followers evolve through a local search, with the leader shifting to the queue's end and the first bird becoming the new leader for the next iteration. This model improves population recombination and leader replacement for faster convergence, using three adjustment strategies to enhance diversity and avoid stagnation in local optima.

Individual development is the advantage of DMBO. Once the birds are organized into the shape of V, every bird can produce a few NSs over mutation and crossover operators, so they can pick a superior distinct from the NS to substitute itself. Unemployed NSs were revealed with subsequent birds to aid its progress. The NS set of the leader bird is denoted as S_{leader}, and the NS set of the right and left subsequent birds are denoted as S_{right} and S_{left}.

(a) Initialize population: Depending upon n-dimension population, n are arbitrarily generated feasible solutions, and the one possible solution denotes a migrant bird.

(b) Build V from a line: Pick a robust individual as the leader bird, and the remaining birds are separated to the right and left sides to create a V form. The right and left lines are signified as B_{right} and B_{left}.

(c) Leader evolution: The leader bird generates various new solutions and stores them in S_{leader}. If any solution surpasses the leader's, it gets replaced; otherwise, the leader remains. Finally, the unexploited NSs are shared with the groups.

(d) Follower evolution: Initially, the followers produce NSs according to the evolution tactic. Then, the model places the NS and solutions handed by the preceding birds into S_{left} or S_{right}. If the individual in S_{left}/S_{right} is superior to the existing follower bird, then the follower is substituted.

(e) Re-combination of the population and re-placement of the leader bird: Once the overall rounds are completed, every migrant bird advances and the initial population integrates with new entities to form a novel set B. The initial population is modified and added to this set to improve convergence toward the optimal solution. The model selects the top n individuals for a new population, designates the best as the leader, and allocates the others accordingly. Moreover, the best individual is stored in an external archive X. The algorithm concludes once the maximum number of iterations is attained.

DMBO is used to optimize the hyperparameters of the DBN model. Performance evaluation is based on MSE:

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \quad (13)$$

where M and L characterize the subsequent values of layer and data, respectively, and y_j^i and d_j^i denote the achieved and appropriate magnitudes for the j^{th} element in the secondary layer of the network with time t.

IV. EXPERIMENTAL VALIDATION

The performance of the DMBODL-CIP method was evaluated using INSAT3D Infrared & Raw Cyclone Images (2012-2021) from [24]. This image dataset encompasses INSAT3D obtained infrared and ray cyclone images through the Indian Ocean in the period 2012 to 2021, with every cyclone image intensity in knots. The proposed technique was tested using Python 3.6.5 on a PC with i5-8600k CPU, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter settings were: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

Table I shows the TC intensity prediction results of the DMBODL-CIP technique on the Training (TRS) and Testing (TSS) sets. Based on MSE, the proposed technique achieved MSE of 71.6542 and 36.2834 under TRS and TSS, respectively. Additionally, it achieved RMSE of 8.4649 and 6.0236 at TRS and TSS, respectively. Meanwhile, the DMBODL-CIP method achieved MAE of 5.7639 and 4.1655 under TRS and TSS. Furthermore, the DMBODL-CIP method achieved MAPE of 0.1131 and 0.0958 under TRS and TSS. Finally, the DMBODL-CIP method achieved NSE of 0.8853 and 0.9272 under TRS and TSS, respectively.

TABLE I. TC INTENSITY PREDICTION RESULTS OF THE DMBODL-CIP MODEL

Metrics	Training Set	Testing Set
MSE	71.6542	36.2834
RMSE	8.4649	6.0236
MAE	5.7639	4.1655
MAPE	0.1131	0.0958
NSE	0.8853	0.9272

The RMSE results of the proposed technique were compared with those of previous models [15, 25-27]. The proposed DMBODL-CIP technique achieved superior performance, with a minimal RMSE of 6.02 kt, improving the prediction of TC intensities.

V. CONCLUSION

This study presented the development of the DMBODL-CIP technique on RSIs. The objective was to estimate the intensity levels of TC utilizing an optimal DL model. The DMBODL-CIP technique initially performs preprocessing in two stages: BF- and AHE-based noise removal and contrast enhancement. Moreover, a deep CNN-based SqueezeNet model is employed for feature extraction. For the prediction of TC intensity, the DMBODL-CIP technique employs a DBN model. Finally, the DMBO model is used for optimum hyperparameter selection of the DBN model. The investigational analysis of the DMBODL-CIP technique was tested on a cyclone image dataset from Kaggle. The comparison study of the DMBODL-CIP technique portrayed a superior RMSE value of 6.02 kt, which is better than existing techniques. Future works may focus on developing more effectual models that balance complexity and interpretability, allowing real-time predictions while addressing limitations in generalizability and responsiveness to dynamic storm conditions.

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