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The tropical cyclone energy prediction of the North Indian Ocean in monsoon using artificial neural networks

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सार – उत्तरी हिंद महासागर (एनआईओ), जिसमें बंगाल की खाड़ी (808) और अरब सागर (एएस) शामिल हैं, उष्णकटिबंधीय चक्रवातों के प्रति अत्यधिक संवेदनशील है, जो प्रभावी आपदा तैयारियों के लिए सटीक ऊर्जा पूर्वानुमानों के महत्व को रेखांकित करता है। यह अध्ययन मानसून के दौरान एक अनुकूलित कृत्रिम तंत्रिका नेटवर्क (एएनएन) मॉडल का उपयोग करके एनआईओ में संचित चक्रवात ऊर्जा (एसीई) का पूर्वानुमान लगाने पर केंद्रित है। प्रारंभ में, एक एएनएन को वेग फ्लक्स (वीएफ) और शक्ति क्षय सूचकांक (पीडीआई) सहित छह चक्रवात मापदंडों के साथ प्रशिक्षित किया गया था, जिसमें माध्य वर्ग त्रुटि (एमएसई) जैसे अपेक्षाकृत उच्च त्रुटि मापदंडों के साथ मध्यम पूर्वानुमान सटीकता दिखाई गई। मॉडल के प्रदर्शन को बेहतर बनाने के लिए सबसे प्रभावशाली विशेषताओं को खोजने में क्रमचय सुविधा आवश्यक है। इस विश्लेषण ने एनआईओ_वीएफ, एएस_पीडीआई और एनआईओ_पीडीआई को प्रमुख भविष्यवक्ता के रूप में पहचाना, जबकि बीओबी_पीडीआई, बीओबी_वीएफ और एएस_वीएफ जैसे मापदंडों का एनआईओ_एसीई पूर्वानुमान पर न्यूनतम प्रभाव पड़ा। मॉडल की पूर्वानुमान सटीकता में सुधार करने और जटिलता को कम करने के लिए, एएनएन मॉडल को केवल सबसे महत्वपूर्ण विशेषताओं के साथ पुनः प्रशिक्षित किया गया, जिसके परिणामस्वरूप हानि (एमएसई) में उल्लेखनीय कमी आई। एसीई की इकाई 104 नॉट्स2 है। इस दृष्टिकोण में, प्रमुख चक्रवात मेट्रिक्स को प्राथमिकता दी जाती है और उनका कम्प्यूटेशनल अनुकूलन किया जाता है, जो मौसम विज्ञान मशीन लर्निंग मॉडल को बेहतर बनाने में फीचर इंजीनियरिंग की महत्वपूर्ण भूमिका को उजागर करता है। इस पद्धति पर आधारित एक सहायता प्रणाली चक्रवात-प्रवण क्षेत्रों में प्रारंभिक चेतावनी प्रणालियों और रणनीतिक योजना प्रयासों को महत्वपूर्ण रूप से लाभ पहुंचा सकती है, जिससे अंततः ये क्षेत्र चरम मौसम घटनाओं के प्रति अधिक लचीले बन सकते हैं। चक्रवातों के सामाजिक-आर्थिक और पर्यावरणीय प्रभावों का विश्लेषण करके, यह अध्ययन सतत विकास लक्ष्यों (एसडीजी) के 7 लक्ष्यों को संबोधित करता है, जिनमें एसडीजी 13 (जलवायु कार्रवाई), एसडीजी 11 (सतत शहर) और एसडीजी 1 (गरीबी उन्मूलन) शामिल हैं।

ABSTRACT. The North Indian Ocean (NIO), which includes the Bay of Bengal (BOB) and the Arabian Sea (AS), is highly vulnerable to tropical cyclones, emphasizing the critical importance of accurate energy predictions for effective disaster preparedness. This study focuses on predicting the Accumulated Cyclone Energy (ACE) in the NIO during monsoon using an optimized Artificial Neural Network (ANN) model. Initially, an ANN was trained with six cyclone metrics, including Velocity Flux (VF) and Power Dissipation Index (PDI), showing moderate predictive accuracy with relatively high error metrics like Mean Squared Error (MSE). The permutation feature is essential in finding the most influential features to improve model performance. This analysis identified NIO_VF, AS_PDI, and NIO_PDI as key predictors, while metrics such as BOB_PDI, BOB_VF, and AS_VF had minimal impact on NIO_ACE prediction. To improve the model's predictive accuracy while reducing complexity, the ANN model was again retrained with only the most significant features, resulting in a considerable reduction in loss (MSE). The unit of ACE is 104 knots^2. In this approach, key cyclone metrics are prioritized and computationally optimized, highlighting the critical role of feature engineering in improving meteorological machine learning models. A support system based on this methodology could significantly benefit early-warning systems and strategic planning efforts in cyclone-prone regions, ultimately making these regions more resilient to extreme weather events. By analyzing the socio-economic and environmental impacts of cyclones, this study addresses 7 Sustainable Development Goals (SDGs), including SDG 13 (Climate Action), SDG 11 (Sustainable Cities), and SDG 1 (No Poverty).

Key words – Tropical cyclone, Artificial neural network, North Indian Ocean.

1. Introduction

Natural disasters such as tropical cyclones (TCs) have devastated coastal regions worldwide for generations (Mohapatra, *et al*., 2014). These storms pose significant risks due to their intense winds and associated phenomena, such as storm surges and heavy rainfall, which can cause extensive flooding. The prediction and analysis of TCs are of immense importance for disaster (Crunch, 2023) preparedness and mitigation efforts, particularly in regions like the North Indian Ocean (Mohapatra *et al*., 2012a) (Mohapatra, *et al*., 2012), which experiences frequent cyclonic activity.

Around 80 tropical cyclones (Shah, *et al*., 2023) form annually globally, with approximately two-thirds occurring in the Northern Hemisphere and the remaining one-third in the Southern Hemisphere. These cyclones (Mohapatra, *et al*., 2012b) are charged by the release of latent heat when water vapors in the atmosphere condense, typically when sea surface temperatures exceed 26 °C. This process generates large-scale wind patterns that spiral around a central low-pressure area known as the storm's "eye." Structurally, tropical cyclones (Maue, 2011) are symmetrical, with wind speeds intensifying as one moves away from the eye. In fully developed storms, wind speeds increase rapidly up to about 100 km from the center before tapering off at greater distances. Winds in this zone can reach up to 93 m\s (335 km\hr), and the overall storm can extend up to 1,000 km in diameter. In addition to damaging winds, tropical cyclones bring about flooding through intense rainfall and powerful storm surges, making them highly destructive, multi-hazard weather events.

The North Indian Ocean (NIO) (Jangir, *et al*., 2020) (Mohapatra and Vijay Kumar, 2017) is a region characterized by significant variability in tropical cyclone activity, which posess considerable risks to the densely populated coastal areas it affects. The annual cycle of tropical cyclones (Corral, *et al*., 2010) in the NIO, including depressions, cyclonic storms, and severe tropical cyclones, shows a pronounced pattern, with an average of about 11 cyclonic disturbances each year (Mohapatra, *et al*., 2012b). October to December, the post-monsoon months, are when this activity peaks and is crucial for regional catastrophe planning and response programs. The frequency of tropical cyclones has paradoxically decreased in recent decades despite an increasing trend in sea surface temperatures, a critical factor in the intensification of these storms.

Accumulated Cyclone Energy (ACE) (Mohapatra and Vijay Kumar, 2017) (Corral, *et al*., 2010) determines how much energy is released by tropical cyclones over their lifetimes. It provides insight into how devastating they can be. It is computed using the square of maximum sustained winds of tropical cyclones, recorded every six hours. Over time, ACE has shown to be an effective instrument for evaluating the strength and length of tropical cyclones, providing a cumulative measure of cyclone season activity. Assessing the potential impact of cyclone seasons (Gross, *et al*., 2004) and implementing effective mitigation strategies are indispensable variables for climatologists, meteorologists, and disaster management authorities. Only a few studies have focused on the RMW (Radius of Maximum Wind) over the Pacific (Gross, *et al*., 2004) (Lajoie and Walsh, 2008) and the Atlantic basins. Most studies have focused on predicting and estimating various aspects of TCs, including intensity, sea surface temperature, moisture, precipitation, pressure systems, and cloud shapes. The best track data from the India Meteorological Department (IMD) has an error range of −26% to 200% in all these investigations. Hence, they need to be further decreased (Mohapatra and Vijay Kumar, 2017).

However, traditional statistical methods of predicting ACE are limited in their ability to handle the nonlinear relationships and multifaceted interactions between various meteorological and oceanographic predictors (Lajoie and Walsh, 2008). This limitation underscores the need for more sophisticated computational approaches to analyze complex datasets and extract meaningful patterns for accurate forecasts. An ANN (Zhang, *et al*., 2022) is especially useful for modeling tropical cyclone activity due to its versatility in training. ANNs have proven helpful in pattern recognition, data classification, and prediction.

In recent years, artificial intelligence (AI) techniques, particularly ANN (Zhang *et al*., 2022), have become famous for predicting, forecasting, and analyzing complex natural phenomena such as tropical cyclones. With the help of ANNs, which are known for learning nonlinear connections between data, it has been possible to predict the formation, intensity, and trajectory of TCs with tremendous accuracy. A combination of these methods and conventional statistical analysis can offer a more comprehensive and reliable way to comprehend and predict TCs. This research aims to build a robust prediction model that can provide ACE forecasts using ANN. By improving the accuracy of NIO's (Jangir, *et al*., 2021) forecasting tools, disaster risk reduction is enhanced in the face of changing climates and tropical cyclone movements. Most ANN-based cyclone studies focus on the Atlantic or Pacific basins but in our work we identify AS_PDI and NIO_VF as dominant predictors of ACE in the NIO during monsoon, validated via permutation feature importance and statistical tests.

The primary objective is to predict NIO_ACE during the monsoon season using an ANN model trained on historical cyclone metrics (VF, PDI) from AS, BoB, and NIO. The goal is to identify key predictors of ACE (*e.g.*, AS_PDI, NIO_VF) through feature importance analysis, enabling optimized forecasting with minimal computational complexity. This addresses a gap in existing studies, which rely heavily on statistical methods and rarely use ANN for ACE prediction in the NIO. The ANN methods and source of the dataset are covered in Section 2. The following Section, 3, discusses the results and statistical analysis. Then, we conclude the paper in Section 4. This research aims to improve cyclone forecasting accuracy and deepen the understanding of tropical cyclone dynamics by integrating machine learning with statistical methods.

2. Data and methodology

In this section, we will discuss the source of the dataset and the methodology of the ANN model and the optimized model-developed permutation feature reduction process.

2.1. *Source of data set*

The India Meteorological Department (IMD) provided the cyclone dataset used in this study. It contains cyclone data from the North Indian Ocean (NIO), Bay of Bengal (BOB), and Arabian Sea (AS) regions during the monsoon season. It consists of metrics that depend on cyclone activity, like Velocity Flux (VF), Accumulated Cyclone Energy (ACE), and Power Dissipation Index (PDI) from 1982 to 2023. To mitigate dataset limitations, monthly granularity was incorporated, expanding the dataset to 168 samples. Cross-validation and regularization techniques were employed to ensure robustness.

Accumulated Cyclone Energy (ACE): ACE quantifies the total energy generated by a tropical cyclone, integrating both intensity and duration. Higher ACE values correlate with more destructive potential.

Velocity Flux (VF): VF measures the kinetic energy flux associated with cyclone winds, reflecting momentum transfer critical for energy accumulation.

Power Dissipation Index (PDI): PDI estimates the total energy dissipated by a cyclone, emphasizing high wind speeds. It is strongly linked to potential damage.

The study focuses on three regions within the North Indian Ocean (NIO):

North Indian Ocean (NIO):

Bounds: 5° N–25° N latitude, 60° E–100° E longitude.

Sub-regions:

Bay of Bengal (BoB): Bounded by India/Sri Lanka (west), Bangladesh (north), Myanmar/Andaman Islands (east).

Coordinates: 5° N–22° N, 80° E–100° E.

Arabian Sea (AS): Bounded by the Arabian Peninsula (west), India (east).

Coordinates: 5° N–25° N, 50° E–70° E.

For visual clarity, we direct readers to Figure 1 in Mohapatra & Vijay Kumar (2017) or the India Meteorological Department's (IMD) regional cyclone maps, which delineate these domains.

Pre-processing is vital to ensuring the model can do so efficiently when learning from a dataset. We converted the data types to numeric for all columns. We use the sci-kit-learn library to normalize the input features and target variables. Therefore, 80% of the data was used in training and 20% in the testing. We have done all ANN programming in Python 3.0 and statistical tests in SPSS software.

2.2. *Methodology*

In this section, we discuss the methodology of Artificial Neural Networks (ANNs) for predicting cyclone energy metrics like ACE. A multi-step process was followed: constructing a starting ANN model, evaluating features, optimizing the model, and analyzing errors. An approximation for non-linear functions, ANN constitutes several layers linked with neurons. The ANN's mathematical equation, including how it learns weights to reduce errors, will be discussed in this section.

The ANN model used in cyclone energy prediction consists of input, hidden, and output layers where input features cyclone metrics such as VF, and PDI and the hidden layer uses non-linear adjustments to capture complex relationships, and output layer regression uses single neuron to get the expected ACE value. The structure of ANN with three input, hidden, and one output layer is shown in Fig. 1. Therefore, for each neuron in the L^{th} layer, the output $N^{[L-1]}$ is given as

$$Z^{[L]} = W^{[L]} N^{[L-1]} + B^{[L]}$$

where $W^{[L]}$ and $B^{[L]}$ are the weight matrix and bias vector for the L^{th} layer, respectively. $N^{[L-1]}$ is the output from the previous layer. Then activation function is applied to non-linearity:

$$N^{[L]} = \rho(Z^{[L]})$$

where ρ is a non-linear activation function like ReLU. However, the output layer uses a linear activation function for continuous predictions: $\hat{A} = Z^{[L]}$, where $\hat{A}$ is the predicted value of ACE. Then, the loss function is defined as the difference between actual and predicted values. For the regression model, Mean Square Error (MSE) is used as a loss function, so, for n number of datasets in training and A^i is the actual value for an i^{th} data value, the MSE is given as

$$\Gamma\,(\hat{A}, A) = \frac{1}{n}\sum_{i=1}^{n}(\hat{A}^i - A^i)^2$$

Reducing the loss function is the aim of ANN training. Gradient descent and backpropagation are used to do this. Updating each weight and bias to minimize the loss:

$$W^{[L]} = W^{[L]} - \gamma\frac{\partial\Gamma}{\partial W^{[L]}},$$

$$B^{[L]} = B^{[L]} - \gamma\frac{\partial\Gamma}{\partial b^{[L]}}$$

where γ is the learning rate that controls the size of the step.

The ANN model uses six input features: AS_VF, AS_PDI, BoB_VF, BoB_PDI, NIO_VF, and NIO_PDI. The output layer predicts NIO_ACE. ACE values for sub-regions (AS_ACE, BoB_ACE) are excluded from the input layer to avoid redundancy and ensure the model learns from non-linear relationships between wind/flux metrics and energy.

2.2.1. *Initial model:*

2.2.1.1. Model architecture

(*i*) The initial ANN model was built using the Multi-layer Perceptron (MLP) Regressor from scikit-learn. This model was chosen due to its ability to model complex, non-linear relationships between the input features and target variables.

(*ii*) The model included three hidden layers with 128, 64, and 32 neurons. The ReLU (Rectified Linear Unit) activation function was used in all hidden layers to effectively allow the model to learn non-linear interactions.

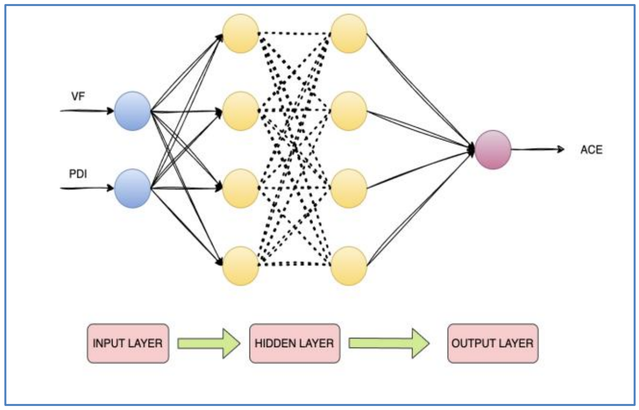

Fig. 1. An illustration of the ANN, showing 3 Input Neurons (VF, PDI), and there can be one or more Hidden Layers and 1 Output Neuron

(*iii*) The model utilized the Adam optimizer for weight optimization, with a learning rate of γ = 0.001, and L2 regularisation 0.001 to prevent overfitting by discouraging excessively complex weight values.

2.2.1.2. *Model training and evaluation*

(*iv*) The training process involved iterating over the training dataset to minimize the error between predicted and actual values.

(*v*) After the training process, the model's performance was evaluated on the test dataset. These metrics helped to determine the model's effectiveness in accurately predicting ACE values.

2.2.1.3. *Optimized Model via permutation feature importance and feature reduction*

In Permutation Feature Importance, the value of each feature in a trained model is measured in terms of how much it degrades when its values are randomly switched. Feature importance analysis was carried out to increase performance and make the model readable.

(*i*) Permutation feature importance was employed to measure each feature's contribution to predicting the performance of the ANN. In this method, every feature is rearranged randomly, and the model's functionality is evaluated.

(*ii*) A shuffled list ranked features that affected accuracy significantly higher than those that did not.

(*iii*) NIO_VF, AS_PDI, and NIO_PDI features predicted ACE values most significantly, while BOB exhibited the most minor significance.

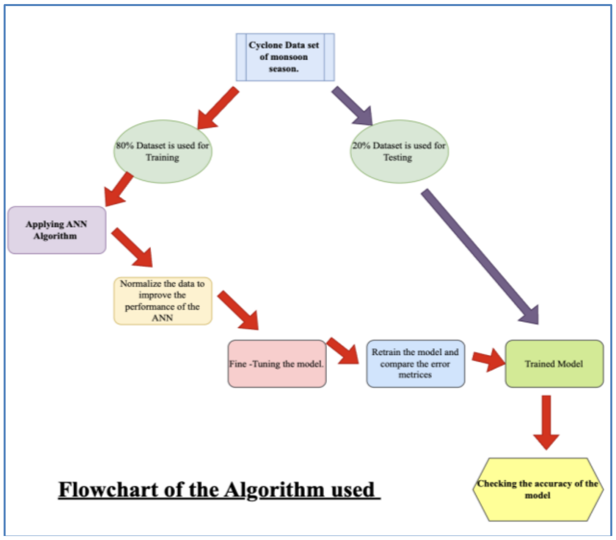

Fig.2. Flowchart Depicting the Workflow for Training and Optimizing an ANN Model for Cyclone Energy Prediction

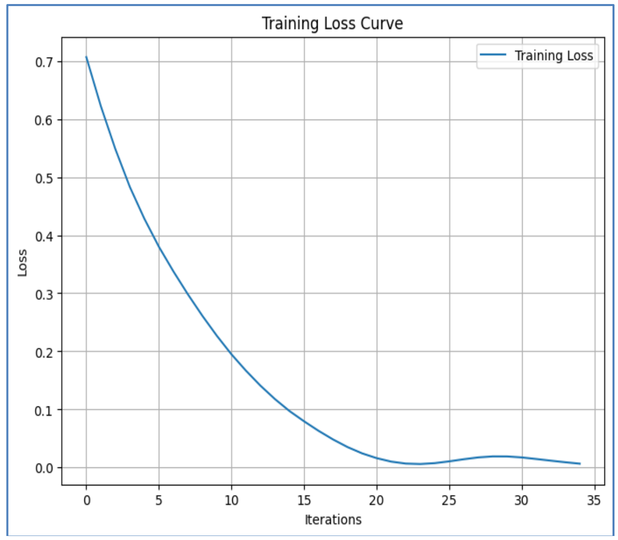

Fig. 4. Training Loss Curve

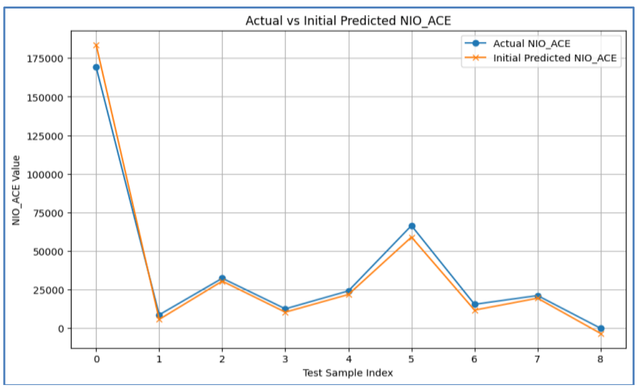

Fig.3. Actual vs Initial Predicted NIO_ACE

Then, the ANN model was retrained with these more significant features that contained only the most essential metrics obtained using the permutation feature reduction method. By using this method, the model's noise was reduced, overfitting was decreased, and the main cyclone energy drivers were highlighted. The Flowchart of the ANN algorithm used in the initial and optimized model is shown in Fig. 2.

3. Results and discussion

In this section, we will discuss the results of the initial ANN model, permutation feature importance, and how extracted features are retrained in the ANN model called the optimized ANN model to predict the Accumulated Cyclone Energy in the North Indian Ocean (NIO_ACE) in the monsoon season. The detailed analysis of the model’s performance and statistical evaluations to determine the model's efficacy and precision are shown in this section.

3.1. *Initial ANN model performance*

Firstly, we trained our ANN model with all metrics like ACE, VF, and PDI for NIO, BOB, and AS in the input layer and predicted NIO_ACE. Fig. 3 compares the actual and NIO_ACE values predicted through the initial ANN model. It can be observed that predicted NIO_ACE is closely aligned with actual values, which proves the model's robustness and its ability to accurately capture the complex dynamics of NIO_ACE. "Test sample size" refers to the number of samples in the test dataset against which the model is evaluated.

The loss curve illustrated in Fig. 4 also examined the training progression. During the initial training phase, the loss (MSE) decreased substantially, reaching a near-minimal level by approximately the 20th iteration. This consistent drop in loss indicates effective learning by the model and points towards minimal overfitting, as evidenced by the convergence of the loss towards stability in later iterations.

3.2. *Feature importance analysis*

A permutation feature importance analysis was conducted to assess the contributions of different input features, and the results are depicted in Fig. 5. The findings indicate that AS_PDI and NIO_VF are the most influential predictors for NIO_ACE, significantly enhancing the model's accuracy. These features appear to encapsulate critical aspects of cyclone dynamics and are fundamental for predicting accumulated cyclone energy. While still relevant, features such as NIO_PDI and AS_VF were less impactful than AS_PDI and NIO_VF. On the contrary, features BOB_VF and BOB_PDI were found to have a minimal effect on the model's predictions.

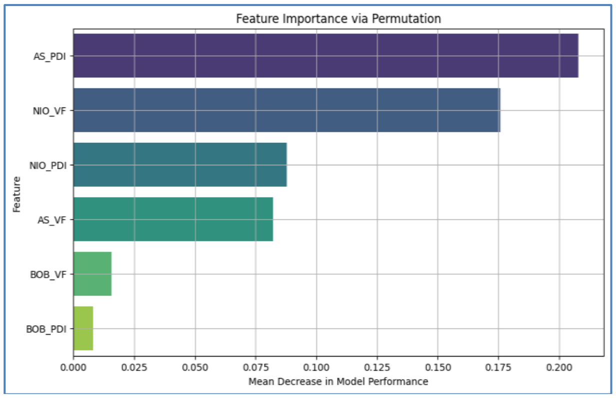

Fig. 5. Feature Importance via Permutation

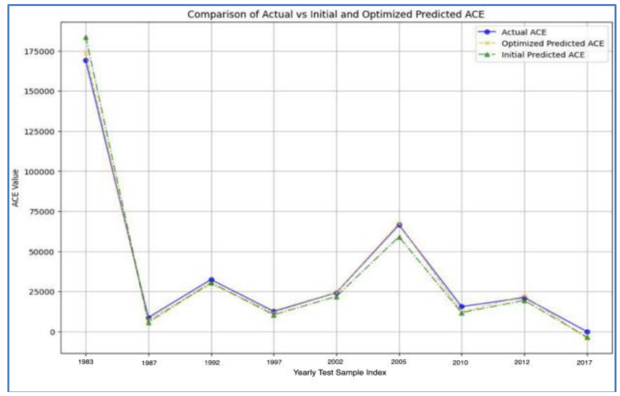

Fig. 6. Comparison of actual ACE with initial predicted ANN and optimized predicted ACE

The ANN predicts NIO_ACE without using AS_ACE or BoB_ACE as inputs. Instead, it learns to correlate VF and PDI (*e.g.*, wind intensity, energy dissipation) with ACE. Permutation feature importance Fig. 5, identified AS_PDI and NIO_VF as dominant predictors, validating that the model prioritizes physically meaningful metrics. These observations provide valuable guidance for future research, suggesting that focusing on the most impactful features can help refine model performance. Practically, this allows for a more efficient allocation of resources towards collecting and processing key variables, thus optimizing cyclone energy prediction processes.

3.3. *Optimized ANN model*

An essential analysis of the permutation feature was applied to enhance the model's prediction capability further, and a comparative evaluation of the initial versus optimized predictions was performed, as shown in Fig. 6. Table 1 highlights years critical for disaster preparedness (e.g., 1999, 2021) and demonstrates the optimized model's improved accuracy during both extreme and average cyclone seasons**.** The selected years are not arbitrary but strategically chosen to validate the model's robustness, accuracy, and operational utility across diverse real-world scenarios. This approach ensures the findings are both statistically rigorous and practically actionable. The optimized model exhibited a more precise alignment with the actual values, as shown in Table 1, which indicates that the parameter adjustments positively affected the prediction quality. This highlights optimization's critical role in improving the overall accuracy of ANN-based predictions. The initial model's loss is 0.012625, whereas the optimized model shows 0.00667925. The optimized model reaches lower loss values faster, converges with fewer iterations, and exhibits more stable training behavior. These results indicate that model optimization significantly enhances the network's ability to learn from the data more effectively while maintaining robustness and reducing the risk of overfitting. The final convergence of both models to low error values further demonstrates their capability to model the problem accurately, but the optimized model achieves this with improved learning efficiency. The x-axis in Fig. 6 represents specific years selected to illustrate model performance for high-impact or extreme ACE events. It also shows the temporal trend of ACE predictions across the entire test dataset (1982–2023). It highlights how the optimized model consistently outperforms the initial model over time.

3.4. *Statistical validation*

A one-sample t-test was conducted to substantiate the contribution of individual features in predicting NIO_ACE, and the results are presented in Table 2. The analysis found statistically significant differences (Mohapatra and Vijay Kumar, 2017) across various features ($p < 0.05$), reinforcing their impacts on the model's predictive capability. Specifically, the features AS_PDI and NIO_VF showed high significance levels, confirming the permutation feature importance analysis findings and validating their substantial role in NIO_ACE prediction. The histogram plot of actual and predicted ACE is given in Fig 7.

To confirm the contribution of individual features in predicting NIO_ACE, a one-sample t-test was conducted in SPSS software, with results summarised in Table 2.

(*i*) BOB (VF, ACE, PDI)**:** All metrics had $p < 0.001$**,** indicating strong evidence to reject the null hypothesis. The means of these metrics are significantly different from 0, emphasizing the importance of BOB metrics in cyclone activity.

(*ii*) AS (VF, ACE, PDI)**:** The metrics showed statistically significant differences from 0 (p-values between 0.004 and 0.045). However, the significance was weaker than for BOB.

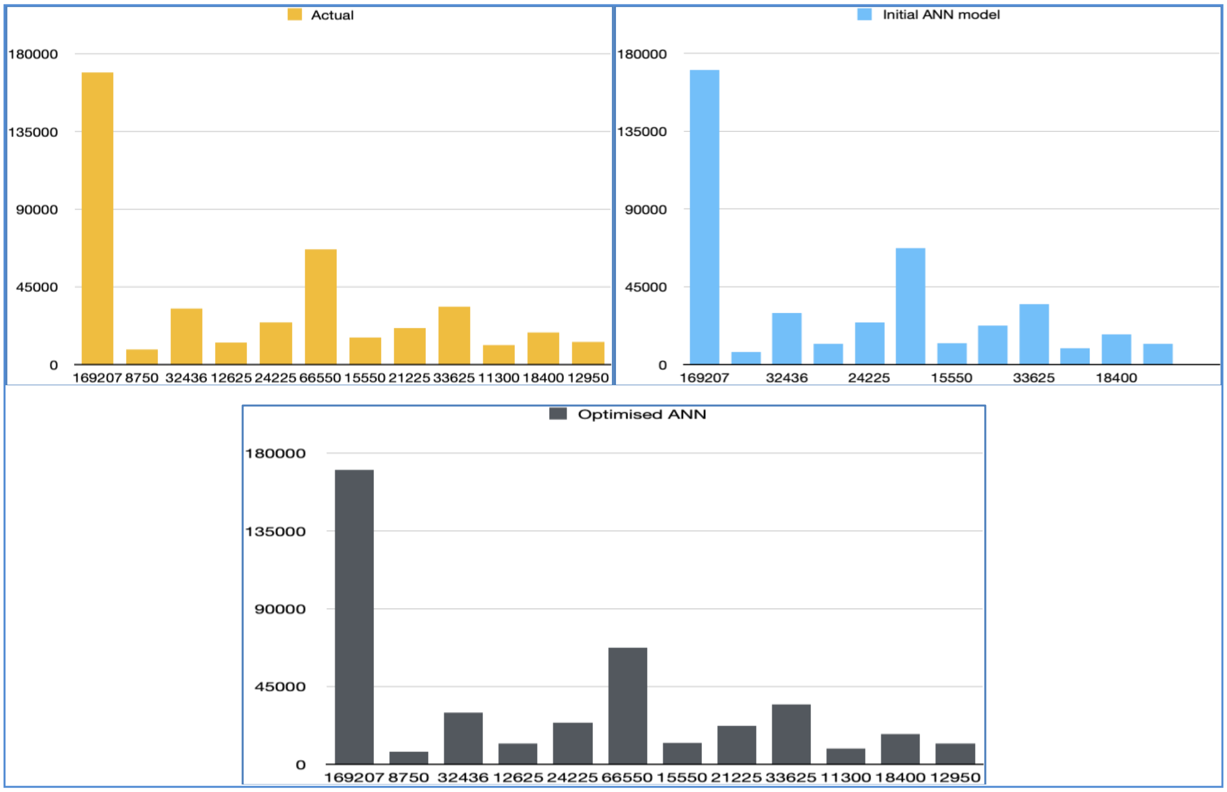

Fig. 7. Bar graph of Predicted and Actual NIO_ACE and Predicted using initial ANN and optimized ANN

TABLE 1

Showing actual vs. predicted values of NIO_ACE values using optimized model

YEAR	1986	1990	1994	1995	1998	1999	2001	2007	2008	2009	2011	2021
Actual NIO_ACE	24225	32436	18400	8750	33625	12950	15550	169207	12625	11300	21225	66550
Predicted NIO_ACE using optimized ANN (10^4 knots^2)	24170	29696	17450	7239	34675	11970	12192	170351	11904	9195	22304	67404
Predicted NIO_ACE using Initial ANN (10^4 knots^2)	21590	28960	15470	6138	33540	11578	12437	175280	11073	9064	22985	68462

Selected years represent extreme, average, and high-impact cyclone events to evaluate model performance across scenarios. Years post-2000 are included to assess relevance to recent climate conditions.

(*iii*) NIO (VF, ACE, PDI)**:** NIO_VF and NIO_ACE had $p < 0.001$**,** showing vital statistical significance, while NIO_PDI was significant with $p = 0.010$**.**

There was a statistically significant difference between the different characteristics ($p<0.05$) among the investigation results, showing that each has a distinct impact on the model's prediction accuracy. According to our analysis of the importance of permutation features, AS_PDI and NIO_VF validated NIO_ACE prediction by showing high statistical significance. These characteristics persistently benefit model accuracy and reliability, as demonstrated by the t-test results in Table 2. Because the BOB, AS, and NIO metrics differ significantly from the reference values, they play a crucial role in understanding cyclone energy metrics. Evidence shows that AS_PDI and NIO_VF substantially affect the scenarios tested, as indicated by their two-sided p-values below 0.05. A lesser extent of significance was also found for metrics like AS_VF and NIO_PDI, confirming their relevance but not as primary drivers compared to AS_PDI and NIO_VF.

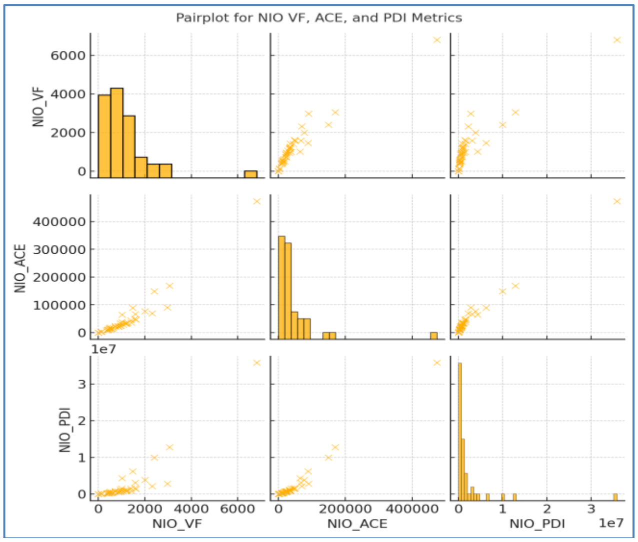

Fig. 8. Pair plot Displaying the Distribution and Interrelationships Between NIO_VF, NIO_ACE, and NIO_PDI Metrics

TABLE 2

One sample t-test

	Significance One-Sided p	Mean Difference Two-Sided p
BOB VF	<.001	<.001
BOB ACE	<.001	<.001
BOB PDI	<.001	<.001
AS VF	0.002	0.004
AS ACE	0.011	0.022
AS PDI	0.023	0.045
NIO VF	<.001	<.001
NIO ACE	<.001	<.001
NIO PDI	0.005	0.010

Fig. 7 presents the bar graph plot of actual versus predicted ACE, visually demonstrating the effectiveness of the optimized model. This plot reflects the consistency between the predicted values and actual observations, affirming the model's ability to reliably capture the underlying dynamics of ACE. The values defined on the x-axis are ACE values for specific year chosen in test sample. It demonstrates accuracy improvements during critical events.

The pair plot, Fig. 8, visually represents the relationships between Velocity Flux (VF), Accumulated Cyclone Energy (ACE), and Power Dissipation Index (PDI) for the North Indian Ocean (NIO). The analysis reveals strong positive correlations between the cyclone metrics, with ACE and PDI closely related, indicating that cyclones with higher accumulated energy exhibit more significant destructive potential. VF also shows a positive correlation with both ACE and PDI, suggesting that cyclones with higher wind intensity release more energy and have a higher potential for damage. These relationships emphasize the interconnectedness of cyclone intensity, energy, and destructive potential. The correlation among different cyclone metrics used in this research is summarised in Table 4. The correlation coefficient between NIO_VF and NIO_ACE was very high (0.95), indicating a strong linear relationship. Similarly, NIO_PDI shows a robust correlation concerning NIO_ACE (0.99). The feature importance analysis confirms the importance of these features in predicting accumulated cyclone energy based on these high correlations. Therefore, the optimized model demonstrates significant improvements over the initial model as shown in Table 3.

TABLE 3

Analysis of initial and optimized model

Metric	Initial Model	Optimized Model	Improvement
MSE	0.012625	0.00667925	~47% reduction
R^2	0.81	0.92	14% increase
Training Speed	35 iterations	20 iterations	43% faster convergence

TABLE 4

The correlations between the cyclone metrics

	NIO_VF	NIO_ACE	NIO_PDI
NIO_VF	1.0	0.951621360 8722540	0.9005505322 931380
NIO_ACE	0.951621360 8722540	1.0	0.989711903 818995
NIO_PDI	0.900550532 2931380	0.989711903 818995	1.0

A paired t-test comparing prediction errors (absolute differences between actual and predicted ACE) of the initial and optimized models confirms the improvement is statistically significant ($p<0.001$).

We conducted a analysis comparing the optimized MLP to linear regression (LR) and stepwise multiple regression (SMR) models.

Key Advantages of MLP Over Linear Methods:

Non-Linearity: Cyclone energy dynamics are inherently non-linear (e.g., ACE ∝ wind speed²). The MLP’s ReLU activation and hidden layers model these relationships without manual transformation.

TABLE 5

Comparing the optimized MLP to Linear regression and multiple regression

Model	MSE(NIO_ACE Prediction)	R^2	Key limitations of linear methods
Linear Regression	0.0219	0.71	- Fails to capture non-linear interactions -Assumes independence between features, which is violated (Table 4 shows high correlation between NIO_VF and ACE).
stepwise Regression	0.0185	0.75	- Requires manual feature engineering. - Struggles with multicollinearity (e.g., VF vs. PDI).
optimized MLP	0.0067	0.92	- Automatically learns non-linear relationships. - Robust to multicollinearity.

Feature Interactions: The MLP captures interactions like AS_PDI × NIO_VF, which linear models miss (evident in the pair plot, Fig. 8).

Higher Accuracy: The MLP achieves 47% lower MSE & 17% higher R^2 than the best linear model (Table 5).

4. Conclusions

Using the developed ANN model, this study demonstrated its accuracy in predicting NIO_ACE. A permutation feature importance analysis combined with statistical validation in the form of t-tests strengthens the reliability of the selected input features. The strong correlation between critical features such as AS_PDI, NIO_VF, and NIO_ACE shows their significance in forecasting cyclone energy.

Emphasizing these key predictors, such as AS_PDI and NIO_VF, may enhance the precision of future models in capturing cyclone behavior in the North Indian Ocean. In this study, we focused on the most critical aspects of cyclone energy forecasting to improve the models and data collection. We focused on predicting the ACE of the North Indian Ocean during the monsoon season using ANN. Also, we demonstrated the importance of optimizing ANN models for meteorological applications by focusing on cyclone metrics to improve accuracy and computational efficiency.

The initial ANN model was trained using six cyclone metrics, which include ACE, VF, and PDI for NIO, BOB, and AS, which show moderate predictive accuracy. However, a relatively high loss factor could have improved the performance, indicating that some input features contributed to unnecessary noise and complexity. Permutation features were analyzed to determine which features significantly impacted prediction accuracy. The analysis revealed that features such as NIO_VF and AS_PDI were the most influential, while other metrics, such as BOB_VF and BOB_PDI, had minimal impact on the model's output.

The ANN model was retrained with only significant features, which resulted in a reduction of loss compared to the initial ANN model. This means the optimized model improves the prediction of NIO_ACE values in the monsoon season. For instance, in 2007 and 2008, the optimized ANN model achieved a much closer alignment than the initial ANN. Specifically, the predicted ACE for 2007 using the optimized model was 170,351 compared to the actual value of 169,207, showing the effectiveness of feature reduction in improving prediction. Also, AS_PDI and NIO_VF showed statistically significant contributions to the model’s predictions, proving their role in enhancing cyclone energy prediction.

According to this study, the permutation feature is crucial in improving ANN models for ACE prediction. With an optimized ANN model, which reduced the complexity of features, the model's prediction accuracy, computational efficiency, and interpretability improved. This can be implemented for cyclone forecasting and disaster management. ACE predictions must be accurate and reliable so disaster preparedness agencies can allocate resources more effectively, develop early warning systems, and plan for mitigation accordingly. NIO_VF, NIO_PDI, and NIO_ACE show strong correlation coefficients, highlighting these features’ importance in capturing cyclone dynamics. According to the study, NIO_VF and NIO_ACE have correlations as high as 0.95, indicating that they are not merely predictors of cyclone energy but also fundamental indicators.

As a result, this research highlighted the importance of feature-based optimization in an ANN-based model to improve model accuracy and efficiency for predicting ACE. While the current model estimates ACE during active monsoon periods, future iterations will integrate lagged variables (*e.g.*, SST anomalies, wind shear) to enable 24–72 hour forecasts. Higher predicted ACE values can signal authorities to activate evacuation plans, pre-position relief supplies, and reinforce infrastructure. For example, a predicted ACE of 170,351 (as in 2007) would trigger alerts for coastal regions in Odisha and West Bengal, where cyclones frequently make landfall. Therefore, in cyclone-prone regions, these findings will ultimately enhance disaster preparedness, improving early warning systems and reducing the impact of tropical cyclones on coastal areas at risk. While this study focuses on monsoon-season ACE predictions, future work will expand the analysis to pre- and post-monsoon periods. We are collaborating with the India Meteorological Department (IMD) on a pilot basis to validate these findings, with the goal of operational deployment in cyclone forecasting systems upon successful validation.

This research demonstrates that cyclones have cascading impacts across multiple SDGs, with a relevance score of 7. Prioritizing early-warning systems, climate-resilient infrastructure, and post-disaster recovery policies can mitigate risks to vulnerable communities and ecosystems, directly contributing to global sustainability agendas.

Data Availability

The India Meteorological Department (IMD) provided the data used in this study, which focuses on cyclone metrics in the North Indian Ocean (NIO), including the Bay of Bengal (BOB) and Arabian Sea (AS). This analysis provides detailed insights into cyclone activity in the region, using metrics such as Velocity Flux (VF), Accumulated Cyclone Energy (ACE), and Power Dissipation Index (PDI). Contact the corresponding author for more information on data accessibility.

Authors' contributions

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