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# Annual Cyclone Trends Prediction in Bay of Bengal – An AI & ML Based Approach.

*Perumālla Venkata Rāma Narendra[1], Ch. Sasank[2], T. Chetan Ram[3], D. Mayuri[4], Y. Gayatri[5], K. Mouneesh[6]*

GMR Institute of Technology, Rajam, Vizianagaram, India

**ABSTRACT:**

Tropical cyclones are among the most destructive natural disasters, making accurate path prediction crucial for early warning systems and disaster preparedness. This study focuses on predicting cyclone trajectories based on historical data recorded at 1-hour intervals. The dataset includes key meteorological parameters such as latitude, longitude, wind speed, and atmospheric pressure which influence cyclone movement. A predictive model was developed using past cyclone data to estimate future cyclone paths. By analyzing historical trajectories and meteorological conditions, this approach enhances the accuracy of cyclone tracking. The results demonstrate that leveraging these parameters can improve the reliability of predictions, aiding authorities in effective disaster management and risk mitigation. This research contributes to advancing cyclone forecasting techniques, ultimately helping to minimize the impact of cyclones on communities and infrastructure.

**Keywords**: Deep Learning, Cyclone Prediction, Machine learning in weather prediction, Wind speed, Atmospheric pressure, Weather Forecasting models, Time series Analysis.

## 1.Introduction:

Tropical cyclones are among the most catastrophic natural disasters, frequently impacting the Bay of Bengal region and posing substantial threats to human life, infrastructure, and regional economies. Countries such as India, Bangladesh, Myanmar, and Sri Lanka are especially vulnerable due to their extensive coastlines and high population densities in coastal zones. The annual trends of cyclone activity in the Bay of Bengal—encompassing patterns in frequency, intensity, duration, and seasonal distribution—are critical for understanding regional climatic behavior and enhancing disaster preparedness strategies.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have introduced promising methodologies for improving the forecasting of such complex natural phenomena. These data-driven approaches provide an alternative to traditional numerical weather prediction (NWP) models, which, while robust, are computationally intensive and often limited in capturing the dynamic and nonlinear nature of cyclone behavior. AI/ML models offer greater flexibility and adaptability by learning from vast volumes of historical data, uncovering hidden patterns and relationships among meteorological variables.

Machine learning techniques—such as decision trees, support vector machines (SVMs), artificial neural networks (ANNs), and time series forecasting algorithms—can be effectively employed to model cyclone behavior. By analyzing historical data on parameters like wind speed, atmospheric pressure, rainfall, latitude, and longitude, these models can identify recurring trends and predict future cyclone paths with improved accuracy. Such approaches also provide critical insights into the evolving characteristics of cyclones, which are increasingly influenced by global climate change.

In this study, we focus on the development of a predictive model to estimate the future trajectories of cyclones in the Bay of Bengal using AI/ML techniques. The model utilizes a high-resolution dataset comprising hourly cyclone records, including key meteorological parameters such as latitude, longitude, central pressure, and sustained wind speed. These parameters play a significant role in determining cyclone formation, intensity changes, and movement paths.

Our primary objective is to enhance the reliability and accuracy of cyclone path prediction to support early warning systems and facilitate effective disaster response. By leveraging historical cyclone trends and machine learning algorithms, we aim to build a robust forecasting model capable of aiding governments, meteorological departments, and emergency management agencies in making timely and informed decisions.

Furthermore, this research highlights the importance of integrating AI-driven solutions into existing forecasting frameworks to mitigate cyclone-induced damages. As climate variability continues to alter storm patterns and intensities, data-driven models provide an adaptive and scalable tool for addressing future challenges in cyclone monitoring and disaster risk reduction.

## 2.Literature review:

The prediction of tropical cyclones, particularly in the Bay of Bengal region, has garnered increasing attention due to the rising frequency and intensity of such events. Traditional statistical models, while useful, often struggle to account for the nonlinear and chaotic behavior of atmospheric systems. In response, deep learning and machine learning techniques have emerged as powerful tools in cyclone prediction, offering enhanced accuracy through their ability to model complex spatiotemporal relationships.

Several studies have applied deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for cyclone detection and forecasting. For instance, researchers have demonstrated the effectiveness of CNNs in extracting spatial features from satellite imagery, while LSTM models have been successful in learning temporal dependencies in cyclone trajectory and intensity patterns. The hybrid combination of CNN and LSTM has also been explored, showing improved performance in capturing both spatial and temporal dynamics simultaneously. Recent works have further incorporated ensemble deep learning architectures and hybrid AI-physics models to refine predictions. These models fuse domain knowledge with data-driven learning, allowing for better generalization in scenarios involving rapid intensification or unpredictable track changes. In particular, ensemble models have shown robustness in minimizing uncertainty by combining the outputs of multiple neural network architectures.

Incorporating environmental variables such as sea surface temperature, atmospheric pressure, wind shear, and humidity has been shown to significantly improve the performance of AI-based cyclone prediction models. Researchers have emphasized the importance of feature engineering and data preprocessing, especially when working with historical datasets like IBTrACS, which contain a wide range of parameters across decades. These enriched models provide better insights into cyclone formation conditions and help identify precursors to cyclone development.

Another significant advancement in the literature is the use of transfer learning and attention mechanisms to enhance model learning efficiency and focus on critical spatiotemporal features. Attention-based models can dynamically weigh the importance of different time steps or locations, improving the model's interpretability and performance. These innovations are particularly beneficial in the Bay of Bengal region, where cyclones often show abrupt changes in intensity and direction within short timescales.

Despite the progress, limitations remain in the generalizability and resolution of existing models. Challenges include the sparsity and inconsistency of historical cyclone data, especially in the pre-satellite era, and the difficulty of capturing extreme cyclone events. Moreover, most models are trained on regional datasets, making cross-basin application challenging. Addressing these gaps requires a focus on multi-source data integration, improved resolution, and region-specific customization of AI models to strengthen disaster preparedness and climate resilience in vulnerable coastal zones.

## 3.Methodology:

### *3.1 Data Source and Region of Study*

This study utilized historical cyclone track data obtained from the **NOAA International Best Track Archive for Climate Stewardship (IBTrACS)**. The region of focus was the **Bay of Bengal**, which is highly prone to tropical cyclones, particularly during the pre-monsoon and post-monsoon periods. The temporal range of the dataset spanned from **1982 to 2023**, covering over four decades of cyclone movement records.

Each cyclone track in the dataset consisted of sequential information including:

- **Latitude (°)**
- **Longitude (°)**
- **Maximum sustained wind speed (m/s)**
- **Minimum central pressure (hPa)**

Additionally, shapefiles representing the cyclone tracks were used for geospatial mapping and visualization.

### *3.2 Data Preprocessing*

The cyclone tracks were first parsed from CSV and shapefile formats. Data cleaning involved:

- Removing missing entries
- Filtering tracks located exclusively in the **Bay of Bengal region**
- Converting wind speeds and pressure readings into consistent units

Subsequently, each cyclone track was segmented into temporal sequences representing the cyclone’s position and intensity over time. For sequence modeling, each cyclone was treated as a **multivariate time series**, where each timestep comprised [latitude, longitude, wind speed, pressure].

All numerical features were **normalized using MinMaxScaler** to fit within the [0, 1] range to enhance neural network convergence. These sequences were then divided into input-output pairs for supervised learning, where:

- **Input**: a fixed number of timesteps (n=4)
- **Output**: the immediate next timestep (t+1)

### *3.3 LSTM Model Architecture*

A **Long Short-Term Memory (LSTM)** neural network was developed to learn spatiotemporal patterns from the cyclone sequences. The LSTM was chosen due to its proven capability to handle time-dependent and sequential data through gated memory units.

**Model Configuration:**

- **Input shape**: (sequence_length=4, features=4)
- **Layers**:
  - LSTM layer with 64 hidden units
  - Dropout (rate = 0.2) to prevent overfitting
  - Dense layer with 4 outputs: [latitude, longitude, wind speed, pressure]

- **Loss function**: Mean Squared Error (MSE)
- **Optimizer**: Adam
- **Activation functions**: Tanh (LSTM), Linear (output)

The model was trained over **50 epochs** with a **batch size of 32**. The dataset was split into training and validation sets in a 75:25 ratio.

### *3.4 Prediction and Evaluation*

Two types of prediction tasks were carried out:

#### 3.4.1 Multi-Step Path Prediction

The model was tested on unseen cyclone sequences to forecast entire paths ahead. Given the initial four observations of a cyclone, the model iteratively predicted subsequent positions by appending each predicted step back into the input sequence.

Predicted tracks were **plotted using Folium** to compare spatial alignment with actual cyclone paths. This provided a visual evaluation of the model's path accuracy.

#### 3.4.2 Next-Point Forecasting

A separate inference module was developed to perform **single-step next location prediction** based on real-time cyclone conditions. This involved feeding a current snapshot [lat, lon, wind speed, pressure] into the model to predict the immediate next location.

This module is designed for **real-time cyclone tracking applications**, where the latest observation is used to forecast the next directional movement.

### *3.5 Visualization and Mapping*

Predicted and actual cyclone paths were visualized using **Folium** (Python-based leaflet mapping tool). Features included:

- **Blue polyline**: historical cyclone path
- **Red polyline**: model-predicted path
- **Markers** indicating start and end locations
- Map centered over the Bay of Bengal for regional clarity

In addition, matplotlib plots were generated to compare:

- Actual vs. predicted latitude/longitude over time
- Wind speed and pressure trends across cyclone lifespan

These visual tools served to validate the LSTM model outputs and interpret error dynamics in both spatial and temporal domains.

## Conclusion and results:

This study implemented a deep learning-based approach to cyclone path prediction using LSTM, applied to historical cyclone data from the Bay of Bengal (1982–2023). The model was evaluated for its ability to predict both cyclone trajectories and the next movement point based on key meteorological inputs.

### *4.1 Training and Evaluation Performance*

The LSTM model was trained for 50 epochs with a mean squared error (MSE) loss function. The final training and validation performance is as follows:

- **Final Training Loss**: 0.0049
- **Final Validation Loss**: 0.0046

The low and closely matched training and validation loss values indicate effective learning and generalization, with minimal overfitting. These results demonstrate that the model successfully captured the temporal dependencies within the cyclone sequences.

### *4.2 Multi-Step Path Prediction*

Given four consecutive historical data points for each cyclone (latitude, longitude, wind speed, pressure), the LSTM model was able to forecast multiple steps ahead in time. Predicted cyclone tracks were plotted alongside ground-truth tracks using Folium.

**Visual Validation**:

- **Red Polylines** represent predicted cyclone paths.
- **Blue Polylines** show the actual IBTrACS historical tracks.

The predicted tracks exhibited strong alignment with actual cyclone trajectories, particularly in capturing curvature, coastal approach directions, and cyclonic turning points. The model showed robustness even during moderate changes in wind speed and pressure.

### *4.3 Next-Point Prediction*

The model also supported real-time forecasting for the **next cyclone position**. Using a single input record (current location, wind speed, pressure), the model produced one-step-ahead predictions of the cyclone's center.

For example, an input of:

- Latitude: 15.0°
- Longitude: 87.0°
- Wind Speed: 80 m/s
- Pressure: 950 hPa

Produced a predicted next location of approximately:

- Latitude: **14.50°**
- Longitude: **86.71°**

This module is ideal for live systems to monitor cyclone shifts using the latest observation, providing high-temporal-resolution forecasts.

### *4.4 Spatial and Temporal Observations*

The model's performance was most accurate when cyclones exhibited consistent patterns in speed and pressure. Cyclones showing sudden curvature or rapid intensification near coastlines posed greater prediction difficulty, indicating potential for incorporating atmospheric context features (e.g., SST, wind shear) in future work.

## 5. Conclusion

This research demonstrates the application of Long Short-Term Memory (LSTM) networks in forecasting cyclone paths in the Bay of Bengal using the IBTrACS dataset. The model effectively captured sequential patterns in cyclone behavior and predicted both full tracks and individual next movement steps based on basic meteorological features.

Key findings include:

- The LSTM model achieved strong performance with minimal error and high spatial fidelity in path reconstruction.
- Next-point prediction capabilities open doors for real-time applications in cyclone monitoring systems.
- Visualization tools confirmed the physical plausibility of the model's predictions and its alignment with historical climatological trends.

While the current framework uses core cyclone variables (lat, lon, wind speed, pressure), the model's performance can be improved with additional meteorological inputs such as sea surface temperature, ENSO indices, or wind shear. Future research may also explore ConvLSTM and attention-based architectures to better capture spatial dependencies.

In conclusion, the integration of LSTM with cyclone datasets offers a promising direction for intelligent disaster forecasting systems. With continued enhancement and regional calibration, such models can contribute significantly to early warning systems and climate resilience in cyclone-prone coastal regions.

**LIST OF PUBLICATIONS (REFERENCES)**


1. Hao, P., Zhao, Y., Li, S., Song, J., & Gao, Y. (2024). Deep Learning Approaches in Predicting Tropical Cyclone Tracks: An Analysis Focused on the Northwest Pacific Region. Ocean Modelling, 102444.
2. Chand, C. P., Ali, M. M., Himasri, B., Bourassa, M. A., & Zheng, Y. (2022). Predicting Indian Ocean cyclone parameters using an artificial intelligence technique. Atmosphere, 13(7), 1157.
3. Sen, S., Nayak, N. C., & Mohanty, W. K. (2023). Long-term forecasting of tropical cyclones over Bay of Bengal using linear and non-linear statistical models. GeoJournal, 88(Suppl 1), 85-107.
4. Kumar, S., Biswas, K., & Pandey, A. K. (2021, May). Prediction of landfall intensity, location, and time of a tropical cyclone. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 35, No. 17, pp. 14831-14839).
5. Singh, O. P. (2007). Long-term trends in the frequency of severe cyclones of Bay of Bengal: observations and simulations. Mausam, 58(1), 59-66.
6. Kushwaha, P., Sukhatme, J., & Nanjundiah, R. S. (2024). Role of Bay of Bengal low-pressure systems in the formation of mid-tropospheric cyclones over the Arabian Sea and western India. Quarterly Journal of the Royal Meteorological Society, 150(762), 2625-2645.
7. Chen, R., Zhang, W., & Wang, X. (2020). Machine learning in tropical cyclone forecast modeling: A review. Atmosphere, 11(7), 676.
8. Wahiduzzaman, M., & Yeasmin, A. (2024). An Assessment of Tropical Cyclone Frequency in the Bay of Bengal and Its Impact on Coastal Bangladesh. Coasts, 4(3), 594-608.
9. Tiwari, G., Kumar, P., Javed, A., Mishra, A. K., & Routray, A. (2022). Assessing tropical cyclones characteristics over the Arabian Sea and Bay of Bengal in the recent decades. Meteorology and Atmospheric Physics, 134(3), 44.
10. Giffard-Roisin, S., Yang, M., Charpiat, G., Kumler Bonfanti, C., Kégl, B., & Monteleoni, C. (2020). Tropical cyclone track forecasting using fused deep learning from aligned reanalysis data. Frontiers in big Data, 3, 1.
11. Yeasin, M., Paul, R. K., & Shankar, S. V. (2024). Ensemble machine learning models for forecasting tropical cyclones in North Indian region. Earth Science Informatics, 17(4), 3705-3714.
12. Rüttgers, M., Lee, S., Jeon, S., & You, D. (2019). Prediction of a typhoon track using a generative adversarial network and satellite images. Scientific reports, 9(1), 6057.