Asian Journal of Applied Science and Technology (AJAST)
Volume 9, Issue 1, Pages 49-63, January-March 2025

Predicting and Classifying Cyclones: Integrating CNN-GRU and BiLSTM for Comprehensive Modeling of Climatic Impacts

Abinaya G.[1], Archana Debi Stella A.[2], Jagasri V.[3] & Suresh Kumar K.[4*]

[1-4]*Department of Information Technology, Sri Krishna College of Technology, Coimbatore, Tamilnadu, India.*
Corresponding Author (Suresh Kumar K.) Email: sureshkumarkskphd@gmail.com[*]

DOI: https://doi.org/10.38177/ajast.2025.9106

Article Received: 21 November 2024 *Article Accepted: 27 January 2025* *Article Published: 30 January 2025*

ABSTRACT

Some of the most disastrous ones among the calamities of nature are cyclones, which really threaten economic stability and also present threats to environmentally sustainable factors. A hybrid deep learning model is developed here, integrating CNN along with GRU for adopting the prediction and Bi-LSTM for the classification of cyclone severity in an effective manner concerned with disaster management and on-time response. The major meteorological parameters that the analysis is considered in the proposed system are as follows: wind speed measured at a height of 10 meters, rainfall, wind direction at the same height, sea surface temperature recorded at 2 meters, atmospheric pressure at 2 meters, and relative humidity also measured at 2 meters. Among these, predictions for cyclone occurrence should be done by using the CNN-GRU model, followed by classification of a cyclone that needs to be classified into the following six classes of severities, namely: "No Cyclone", "Minimal", "Moderate", "Extensive", "Extreme" and "Catastrophic by BiLSTM. High-quality inputs for the models were ensured through extensive preprocessing steps, which included normalization and feature extraction. For all the classification models, evaluation was conducted using performance metrics such as precision, recall, F1-score, and accuracy. Additionally, RMSE and MAE were utilized to assess the precision of the predictions. Results from experiments guarantee that our approach of a hybrid would lead to the best and perform over state of-the-art traditional methods along with one stand-alone machine learning model regarding the classification task in totality, which was done with 87% accuracy. These results justify that the proposed model will be very helpful to meteorological departments and disaster management. A system with state-of-the-art machine learning techniques improves forecasting for better preparedness toward cyclones and risk mitigations. The incorporation of CNN-GRU and the BiLSTM models depicts how hybrid deep learning frameworks have considerable potential to solve complex climate challenges and hence are a significant step toward environmental risk management.

Keywords: Cyclone prediction; Deep learning; Classification; Accuracy; CNN-GRU; Bi-LSTM; Disaster management.

1. Introduction

Cyclones rank among the most formidable natural disasters, posing significant challenges to human life, infrastructure, and ecological balance throughout history. The atmospheric cyclone is developed due to the interaction between complex meteorological factors, high wind, heavy rainfall, and storm surges that may be very destructive for coastal and interior areas [1]. Understanding and predicting cyclones is an important task in meteorology, which requires advanced computational techniques and a great amount of data analysis. Deep learning has brought new paths toward the solution of this problem, achieving unparalleled performance in prediction and classification using high-dimensional datasets [2].

With a continued alteration in the globe's climate, cyclones are increasing in frequency and strength along with rising sea surface temperatures and changing atmospheric patterns. That upward trend signifies an increase in need for dependable models that forecast the occurrence and, much more important, classify their intensities [3]. Predictions for a coming cyclone become indispensable in disaster preparedness in order to make effective the various operations like evacuation of the area, allocation, mobilization, and distribution of resources according to priorities, mitigation planning and so on. The prediction of the severity of a cyclone would, in return, indicate the possible impacts in consideration of designing targeted intervention [4]. In this context, the field of cyclone prediction and classification has evolved through various stages over the years. Previous methods relied a great deal on empirical models and statistical techniques. Although helpful, most of these empirical models could not capture the nonlinear dynamic relations in the meteorological data [5]. The machine learning rise has been considered as something different because it could model learning complex relationships between variables straight from the data. Among these, deep learning has proven to be an especially effective method for processing large datasets and uncovering complex patterns that were previously inaccessible. It studies the integration of deep learning approaches in order to solve two major problems: the prediction of cyclones and the classification of its severity [6]. The model employs a hybrid architecture combining Convolutional Neural Networks and GRU, while the classification is performed using a Bidirectional Long Short-Term Memory network. The selection of these models is based on their strengths: CNNs are highly effective in extracting spatial features from the data, while GRUs are well-suited for capturing temporal dependencies [7]. In that respect, BiLSTM is advantageous in the analysis of patterns which come both forward and backward. Together, these models form a very good basis on which to analyze the spatiotemporal characteristics of cyclones.

The study takes into account several factors, including wind speed, rainfall, wind direction, sea surface temperature, sea level pressure, and relative humidity. All these factors contribute to cyclone formation and intensification [8]. Wind speed and direction reflect directly on the kinetic energy and track of the cyclone, whereas rainfall is indicative of the flooding potential. Sea surface temperature acts as a very critical driver in cyclone formation since the warmth of the ocean waters provides energy for the development of cyclones. Sea level pressure and relative humidity are other modifiers that shape the dynamics of cyclones in terms of intensity and movement [9]. A key challenge in cyclone modeling lies in the data, which is both dynamic and diverse in nature. A cyclone is influenced by many variables that are interdependent and evolve over time, thus making it a complex, high-dimensional dataset. The temporal aspect further adds to the complexity of this data, as the models need to account for changes over time while considering spatial correlations between attributes. In tasks with sequential data, deep learning models prove to be appropriate [10]. The CNN-GRU model combines the spatial feature extraction by CNN with the sequential modeling by GRU, which is thus suitable for capturing spatiotemporal dynamics in cyclone data.

The CNN-GRU model follows the methodology of finding some pattern related to cyclone occurrence chances in historical data. It first uses CNN layers for identifying the spatial features high wind speed or high sea surface temperature-that are indicative of the formation of cyclones [11]. Then, these features are fed into the GRU layers, which model their temporal progression, capturing the sequential dependencies critical for accurate prediction. Such hybrid architecture not only increases the accuracy of the forecast but also provides an insight into the driving factors behind cyclone formation. On the other hand, the BiLSTM model targets the classification of the severity of cyclones. The architecture of a BiLSTM is bidirectional; it considers both forward and backward flow in temporal data and has been quite effective in applications where both past and future contexts are relevant [12]. This capability, in the context of classification of cyclones, has enabled the model to estimate the severity more accurately by considering the complete temporal context of the attributes with respect to wind speed, pressure, and rainfall. Therefore, cyclones are classified into categories such as minimal, moderate, extensive, extreme, and catastrophic using the BiLSTM model, with this crucial information being provided to assist in disaster management and mitigation efforts [13]. Such models, when integrated, mark a major milestone in the field of meteorology. Most traditional systems on cyclone prediction and classification have always faced many difficulties due to the complexity and huge volumes of data involved in this task and often simplify the problems in their assumptions, hence a loss of accuracy [14]. In contrast, deep learning methods presented in this study have a much greater capability to deal with large-sized and high-dimensional data for revealing intrinsic patterns with quite remarkable precisions in prediction and classification. This capability is very important within the context of climate change, where cyclones become increasingly unpredictable. One of the most important elements in this research is the preprocessing of data so that it may be compatible with deep learning architectures [15]. Most raw cyclone data contains a lot of noise and is inconsistent, hence needing heavy preprocessing to make any meaningful feature extraction from it. Techniques used to standardize the data include steps like normalization, scaling, and encoding, which reduce biases in the data and increase model performance. Preprocessing is one area that has great importance because the basis of the models doing proper and reliable predictions depends on it [16].

Another challenge that this paper has attempted to address relates to class imbalance, which, as such, is inherently a common problem in the cyclone severity classification. Some classes might be very few in a dataset, such as "minimal" or "catastrophic," that are very few in this dataset; hence, most of the models fail to generalize over all classes [17]. Data augmentation and advanced loss functions have been employed to mitigate these issues. These measures ensure that all severity levels are well represented, thus enabling the models to perform well in a balanced manner across the categories. Evaluation of the models is made through various metrics: precision, recall, F1-score, and accuracy [18]. This set of metrics gives an all-rounded view of strengths and weaknesses, thus showing where more work may be required to further improve the models. The CNN-GRU model gives a good performance for the cyclone event forecast, whereas it usually struggles to choose between closely related classes. Meanwhile, BiLSTM works very well on this classification task, particularly for "Hurricane" and "Tropical Storm" as major classes, while less frequent classes have to be treated with further measure [19]. The most important implications of the findings from this study would go to disaster management and climate science. Precise cyclone forecasting by authorities can give warnings much in advance, and thus loss of life and property is minimum. Thus, the severity classification gives full insight into the potential impacts that guide resource allocation and targeted interventions. The methodologies developed in this work will further be adapted to other meteorological phenomena, such as hurricanes, typhoons, and extreme weather. The cyclone prediction and classification is mentioned in Table 1 and the severity distribution is mentioned in Figure 1.

Table 1. Cyclone Prediction and Classification Table

Pressure (hPa)	**Wind Speed (km/h)**	**Classification**
1015	20	No Cyclone
1000	60	Minimal
990	90	Moderate
980	120	Extensive
970	150	Extreme
950	180	Catastrophic

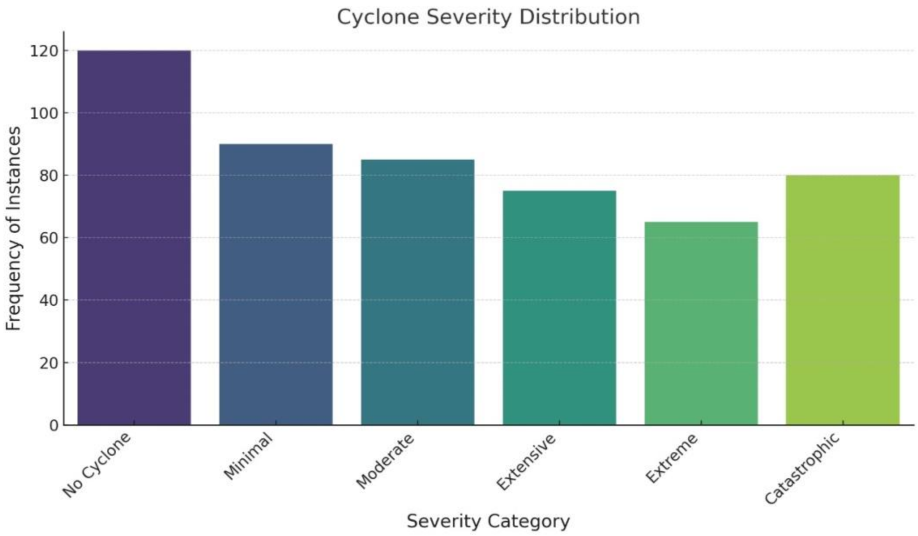

Figure 1. Cyclone Severity Distribution

2. Literature Survey

2.1. Existing System

Deep learning thus brought an enormous transformation in studying cyclone prediction and classification, using sophisticated neural network architecture with varied meteorological data. These approaches overcome some of the major challenges in the prediction of complex natural phenomena, enhancing the accuracy and reliability of forecasts. This multitask learning framework that combines CNN and RNN is able to predict trajectories and intensities of cyclones simultaneously [20]. These models, while executing their various tasks by reusing their features, hence optimize performances that allow full insight into cyclone behaviours, contribute to operational forecasting, and disaster preparedness.

The methods involving CNN, which have been most successful in terms of the early detection of cyclone patterns, have been those applied for global satellite imagery. Such methods will be able to look for features within the high-resolution images that are characteristic of cloud structures and wind patterns, easily facilitating early warnings to increase efficiency in weather monitoring systems [21]. Their training on different datasets from diverse regions enhances the robustness of these CNN models in applying them for detecting cyclones under variable environmental conditions. Early detection capability is very crucial for reducing the impacts of cyclones through timely alerts to the affected populations.

Bi-LSTM models have been very efficient in analyzing time-series data of cyclones. Bi-LSTMs consider both past and future dependencies in the sequences, hence giving better results than other methods used so far for the prediction of cyclone intensity. This is coupled with a couple of nature-inspired optimization techniques emanating from nomadic behaviors that would further enhance the predictive capabilities of the Bi-LSTM model [22]. These indeed allow insight into the nuanced changes with time in the intensity of a cyclone, therefore aiding in disaster response planning. These ensemble methods using multiple CNN models try to identify specific features, such as the formation of the cyclone eye. The cyclone eye is a key indicator of the intensity and structure of a cyclone. High-resolution satellite imagery has become very instrumental in enhancing the accuracy of classification by these models, especially for cyclones at their developmental stages [23]. It allows for the close analysis and detection of those features, thus enabling an estimation of the intensity, hence the understanding of a cyclone's potential.

Hybrid deep learning models that combine those two with Bi-LSTMs are some of the efficient emerging solutions to analyze these data from multichannel satellites, integrating both spatial and temporal data in the capture of dynamic interactions within the atmosphere in driving cyclone behavior [24]. Coupled with this, hybrid models that combine spatial features, such as cloud formations, with temporal patterns in wind speed and pressure form a robust framework for the intensity predictions of cyclones. This spatiotemporal integration is key to understanding the multi-faceted nature of cyclones and enhancing the reliability of forecasts.

AI-driven innovations in the field have also bestowed methodologies involving GNN and advanced RNNs on cyclone prediction and classification. Modern techniques integrate meteorological data such as temperature, pressure, wind speed, and humidity with machine learning algorithms [25]. By capturing the intricate relationships among these variables, GNNs and RNNs enhance climate modeling accuracy, improving cyclone trajectory and intensity predictions. These advancements pave the way for AI to revolutionize traditional meteorological practices, creating highly efficient and scalable systems. Beyond prediction and classification, these frameworks play a vital role in operational forecasting, disaster management, and real-time early-warning systems [26].

Furthermore, these technologies contribute to a deeper understanding of climate variability and its influence on cyclone behaviour. By analysing extensive historical weather data, deep learning models uncover trends that aid researchers in assessing the potential effects of climate change on cyclones over the long term. This insight is invaluable for policymakers and strategists in mitigating the impacts of extreme weather events. Consequently, advancements in deep learning have significantly enhanced cyclone forecasting and classification, offering unmatched accuracy and reliability. Multi-task learning frameworks, CNNs, Bi-LSTMs, GNNs, and hybrid models play a crucial role in advancing cyclone prediction capabilities. By integrating diverse datasets with advanced algorithms, these technologies address key challenges in meteorology, disaster management, and climate research. As deep learning continues to evolve, cyclone prediction will become even more precise, offering greater protection for communities against the devastating effects of tropical cyclones.

3. Proposed System

This research proposes an innovative hybrid deep learning framework that combines convolutional neural networks, graph neural networks, and bidirectional long short-term memory for cyclone forecasting and classification. The framework aims to accurately predict the occurrence of cyclones within a year, along with their trajectory and intensity, while categorizing them into six groups: "No Cyclone," "Minimal," "Moderate," "Extensive," "Extreme," and "Catastrophic." By integrating these three distinct models into a unified approach, the framework effectively performs spatial feature extraction, incorporates relational modeling, and addresses temporal dependencies to deliver a comprehensive final output.

3.1. Architecture of the Proposed System

The process begins with data collection and preprocessing of datasets, including satellite imagery, cyclone track information, and meteorological parameters such as wind speed, temperature, and pressure. Preprocessing steps involve noise removal, normalization, addressing missing data, and dataset augmentation to enhance the robustness of the models. To ensure a fair and balanced evaluation of model performance, the dataset is divided into 60% for training and 40% for testing. During training, CNN, GNN, and Bi-LSTM individually learn patterns from the data. In the testing phase, the models are evaluated for their ability to generalize to unseen data. The architecture of the proposed system is illustrated in Figure 2.

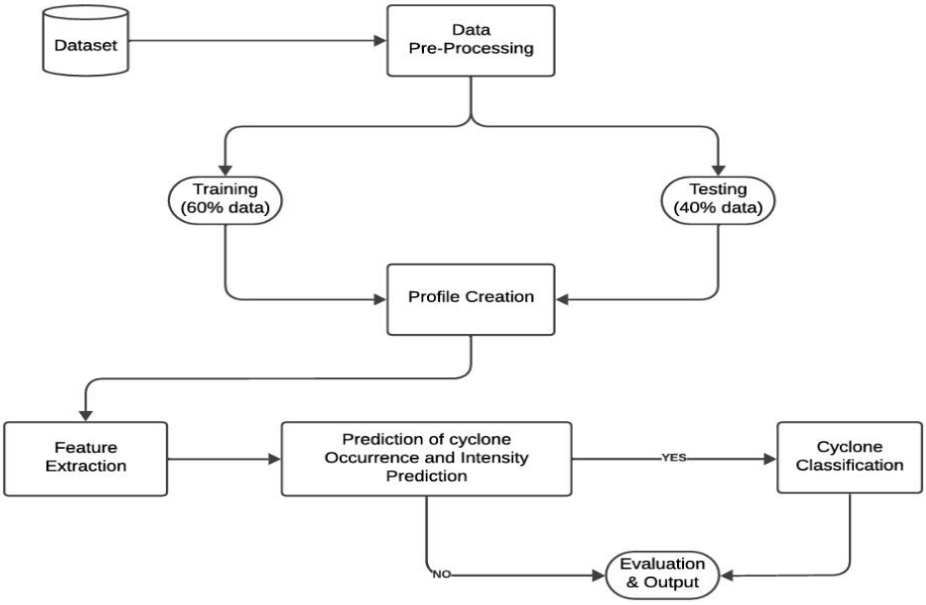

Figure 2. Architecture of the Proposed System

Spatial features in the form of cloud formation, wind patterns, and cyclone eye structure are identified from the satellite images that are fed into the CNN model. These spatial features are very important for the understanding of physical cyclone characteristics. The GNN model analyzes the relationships among meteorological variables, such as pressure and wind speed, and geographic points to capture the spatial dependencies in cyclone tracks. GNNs allow for relational reasoning, an important factor in the prediction of cyclone trajectories and intensities. These modules, consisting of CNNs and GNNs, thereby work in unison for the estimation of occurrence, trajectory, and intensity related to a cyclone. Bi-LSTM models, on other side, use time series of meteorological data-pressure fluctuation, variation of the wind speed with time-and classify cyclones into these six grades of severity class By capturing temporal dependencies in the data, Bi-LSTM ensures that even for evolving systems, cyclone severity is classified correctly. The model's performance in prediction tasks is evaluated using metrics such as accuracy, precision, recall, F1-score, and mean absolute error (MAE). Classified outputs and predicted trajectories are visualized to provide actionable insights for disaster response teams.

3.2. Software Description

Jupyter Notebook is the platform used for the experimentation process as it is an interactive environment that enables the easy implementation of advanced machine learning models, such as CNN, GNN, and Bi-LSTM, for prediction and classification of cyclones. It combines code, visualizations, and documentation in one place, hence providing an integrated platform for data preprocessing, model training, and evaluation. Python's libraries like Pandas and NumPy can handle cyclone datasets efficiently, cleaning, feature extraction, and analysis. With libraries

Volume 9, Issue 1, Pages 49-63, January-March 2025

such as Matplotlib and Seaborn, one can visualize cyclone trajectories in detail, along with their intensity patterns and temporal trends.

For CNNs, Jupyter supports both TensorFlow and PyTorch, which enable the creation of models to analyze satellite images by identifying patterns such as cloud formations and cyclone eye structures. GNNs, implemented via PyTorch Geometric or DGL, model cyclone data as graphs and capture the spatial dependencies of nodes and edges that model relations such as wind and pressure patterns. Bi-LSTM, implemented using Keras or PyTorch, leverages temporal data to classify cyclones into categories such as tropical storms or hurricanes by considering past and future data contexts for better classification.

Jupyter also enhances research documentation by integrating Markdown for explanations and LaTeX for equations, creating a detailed, self-contained workflow. Real-time feedback on model training metrics, such as accuracy and loss, aids in optimizing model performance. Visualizing results, like confusion matrices or CNN feature maps, improves interpretability. With GPU/TPU integration, Jupyter supports efficiency in handing large datasets and intricate models, while compatibility with online platforms makes collaboration or sharing easier. By amalgamating an overview of functionality, flexibility, and user interface, Jupyter Notebook therefore reduces the implementation cycle of models like CNNs, GNNs, and Bi-LSTMs, streamlining research with regards to documentation and reproducibility on cyclone classification.

4. Result and Discussion

A. Standard Scaler (Normalization)

Normalization ensures that each feature contributes equally to the model's performance by scaling the data.

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}$$

Where:

μ: Mean of the feature.

σ: Standard deviation of the feature.

B. Label Encoding

Label encoding converts categorical variables into numerical ones:

$$y_{\text{encoded}} = f(y)$$

Where:

f maps each category (e.g., 'HU', 'TS') to an integer (e.g., 'HU' = 0, 'TS' = 1).

C. One-Hot Encoding

One-hot encoding transforms integer labels into binary vectors:

$$y_{\text{one-hot}}[i, j] = \begin{cases} 1, & \text{if } j = y_{\text{encoded}}[i] \\ 0, & \text{otherwise} \end{cases}$$

ISSN: 2456-883X

Asian Journal of Applied Science and Technology (AJAST)
Volume 9, Issue 1, Pages 49-63, January-March 2025

The confusion matrix for the BiLSTM predictions is discussed in Figure 3.

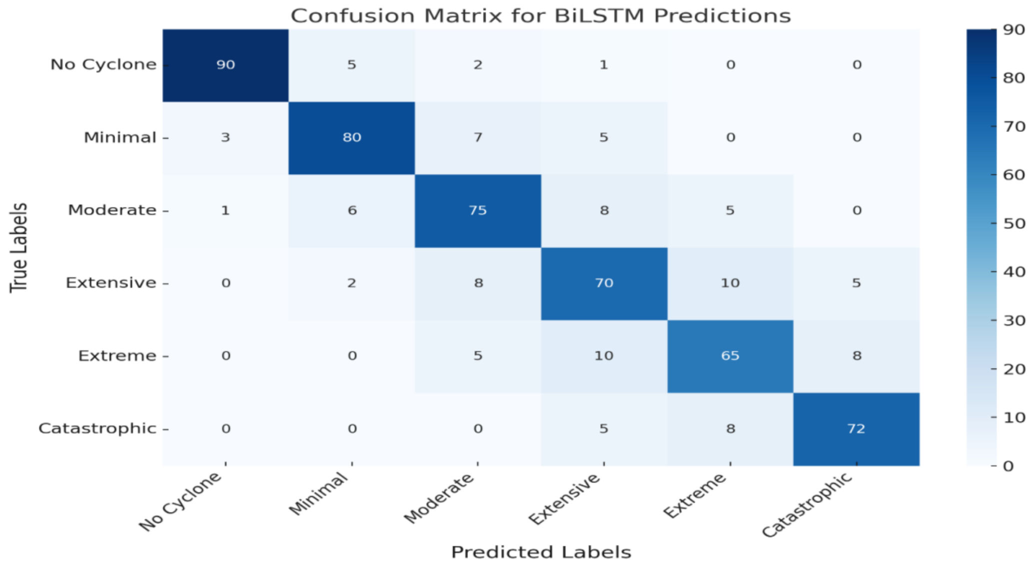

Figure 3. Confusion Matrix for BiLSTM

The table, which mentioned the statistics of the key features, are shown in Table 2.

Table 2. Statistics of Key Features

Feature	Mean	Std Dev	Min	25%	50%	75%	Max
Maximum Wind	52.99	28.66	-98.02	35.98	45.98	70.98	165.98
Minimum Pressure	-250.29	965.43	-997.88	-997.88	-997.88	991.12	1025.12
Sea Surface Temp (2m)	300.27	4.47	291.97	297.97	299.97	302.47	306.97
Relative Humidity (2m)	77.87	17.97	32.67	67.67	78.67	87.67	101.67

D. CNN + GRU Model

Convolutional Neural Network (CNN)

CNN extracts spatial features from the input data using the formula:

$$y_{conv}^{(l)}[j] = \sigma\left(\sum_{i=1}^{k} w_i^{(l)} x_{j+i-1} + b^{(l)}\right)$$

Where:

K: Kernel size.

$w_i^{(l)}$: Weights of the i-th kernel.

$b^{(l)}$: Bias.

σ: Activation function (ReLU).

The CNN-GRU training and validation accuracy which is predicted over various epochs are shown in Figure 4.

Asian Journal of Applied Science and Technology (AJAST)
Volume 9, Issue 1, Pages 49-63, January-March 2025

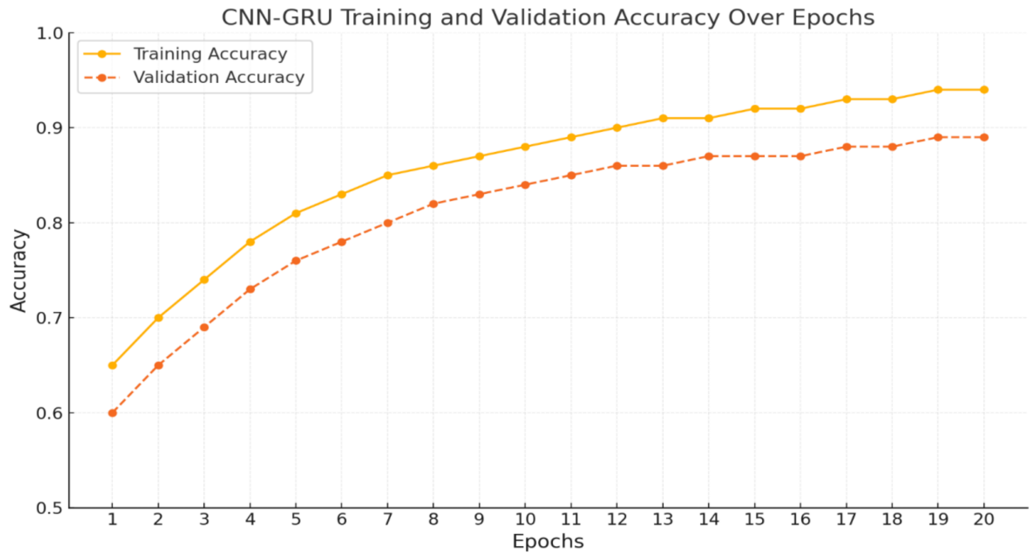

Figure 4. CNN-GRU Training Accuracy

MaxPooling

Pooling reduces the spatial dimensions:

$$y_{pool}[j] = \max(y_{conv}[j: j + p - 1])$$

Where

p is the pooling size.

GRU (Gated Recurrent Unit)

GRU processes sequential data effectively:

$$z_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad \text{(update gate)}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad \text{(reset gate)}$$

$$\tilde{h_t} = \tanh(W_h x_t + r_t \odot (U_h h_{t-1}) + b_h) \quad \text{(candidate activation)}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h_t} \quad \text{(hidden state)}$$

Where:

σ: Sigmoid activation.

$\odot$: Element − wise multiplication.

z_t, r_t: Update and reset gates.

h_t: Hidden state.

Dense Layer (Softmax Activation)

$$y_{output,i} = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Asian Journal of Applied Science and Technology (AJAST)
Volume 9, Issue 1, Pages 49-63, January-March 2025

BiLSTM Model

LSTM Cell

LSTM improves on RNN by incorporating memory mechanisms which is shown in Figure 5.

$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$ (forget gate)

$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$ (input gate)

$\tilde{c_t} = \tanh(W_c x_t + U_c h_{t-1} + b_c)$ (candidate memory)

$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c_t}$ (cell state)

$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$ (output gate)

$h_t = o_t \odot \tanh(c_t)$ (hidden state)

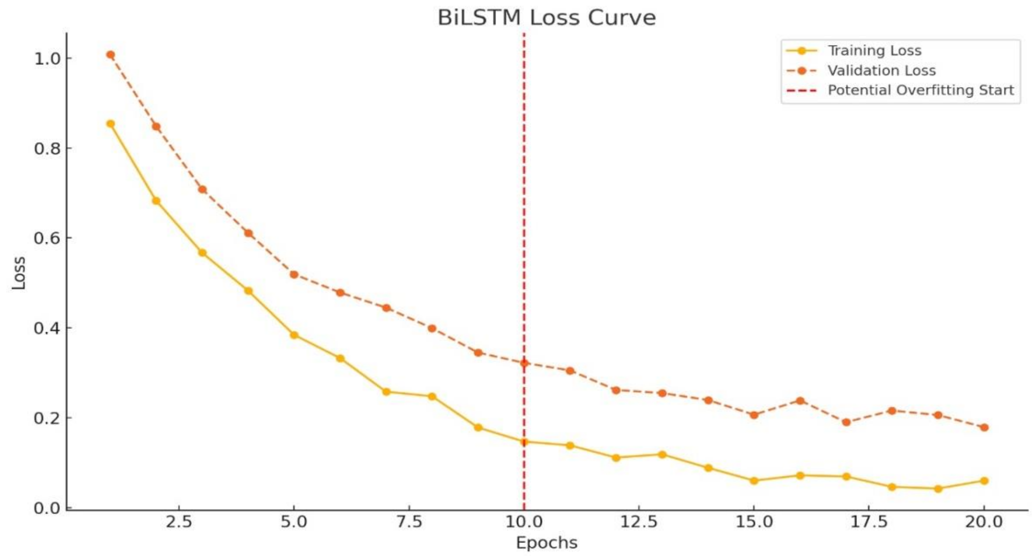

Figure 5. BiLSTM Loss Curve

4.1. Metrics

Accuracy

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}}$$

The correlation matrix for the determination of the accuracy is shown in Table 3.

Table 3. Correlation Matrix of Key Features

Feature	Maximum Wind	Minimum Pressure	SST (2m)	RH (2m)
Maximum Wind	100	-85	65	55
Minimum Pressure	-85	100	-60	-45
Sea Surface Temp (2m)	65	-60	100	50
Relative Humidity (2m)	55	-45	50	100

Classification Report (Precision, Recall, F1-Score)

Precision:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-Score:

$$\text{F1} - \text{Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The classification metrics for the BilSTM is shown in Table 4.

Table 4. Classification Metrics for BiLSTM Model

Metric	**Precision**	**Recall**	**F1-score**
No Cyclone	94	97	96
Minimal	91	93	92
Moderate	89	87	88
Extensive	86	82	84
Extreme	94	97	96
Catastrophic	86	86	82

Then the overall report predicted in various categories is shown in Table 5.

Table 5. Classification Report

Category	**Precision**	**Recall**	**F1-Score**	**Support**
DB (Disturbance)	6	8	5	25
EX (Extratropical)	86	8	12	567
HU (Hurricane)	101	104	102	765
LO (Low)	70	69	70	234
SD (Subtropical Depression)	1	4	9	45
SS (Subtropical Storm)	8	1	2	126
TD (Tropical Depression)	91	102	96	1764
TS (Tropical Storm)	86	104	94	3742
WV (Wave)	4	6	87	34

The analysis result is displayed in Figure 6.

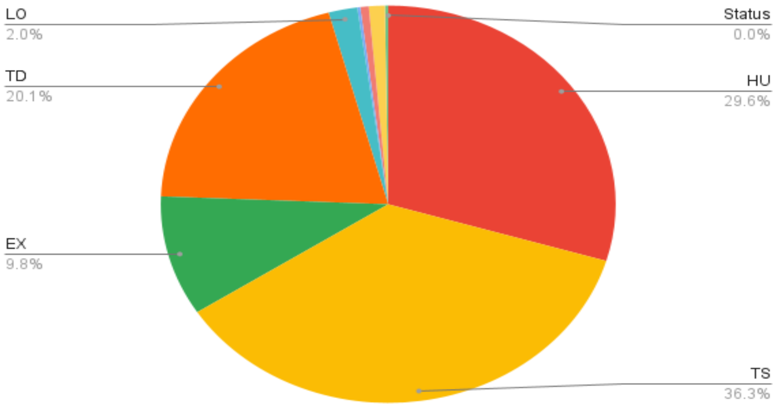

Figure 6. Analytical Result

5. Conclusion

The proposed hybrid deep learning model integrating CNN-GRU for cyclone prediction and Bi-LSTM for severity classification proves to be an effective approach for disaster management. By leveraging key meteorological parameters such as wind speed, rainfall, sea surface temperature, atmospheric pressure, and relative humidity, the model ensures accurate forecasting of cyclone occurrence and severity classification into six levels. Extensive preprocessing, including normalization and feature extraction, enhanced input quality, leading to improved predictive performance. Experimental results demonstrated an accuracy of 87%, outperforming traditional and standalone machine learning models. The use of RMSE and MAE metrics further validated the precision of the predictions. This study highlights the significance of deep learning in meteorology, enabling proactive risk mitigation and timely response. The integration of CNN-GRU and Bi-LSTM establishes a robust framework for addressing climate challenges, making it a valuable tool for meteorological departments and disaster management agencies to enhance preparedness and minimize cyclone-related impacts.

Declarations

Source of Funding

This study did not receive any grant from funding agencies in the public, commercial, or not–for–profit sectors.

Competing Interests Statement

The authors declare no competing financial, professional, or personal interests.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors made an equal contribution in the Conception and design of the work, Data collection, Simulation analysis, Drafting the article, and Critical revision of the article. All the authors have read and approved the final copy of the manuscript.

Availability of data and material

Authors are willing to share data and material according to the relevant needs.

References

[1] Rezaie Ali Mohammad, Celso Moller Ferreira & Mohammad Rezaur Rahman (2019). Storm surge and sea level rise: Threat to the coastal areas of Bangladesh. In Extreme Hydroclimatic Events and Multivariate Hazards in a Changing Environment, Pages 317–342, Elsevier.

[2] Pedro Francisco (2023). A review of data mining, big data analytics, and machine learning approaches. Journal of Computing and Natural Science, 3(4): 169–181.

[3] Barlow Mathew, William J. Gutowski, John R. Gyakum, Richard W. Katz, Young-Kwon Lim, Russ S. Schumacher, Michael F. Wehner, et al. (2019). North American extreme precipitation events and related large-scale meteorological patterns: a review of statistical methods, dynamics, modeling, and trends. Climate Dynamics, 53: 6835–6875.

[4] Yadav Devendra, K., & Akhilesh Barve (2019). Prioritization of cyclone preparedness activities in humanitarian supply chains using fuzzy analytical network process. Natural Hazards, 97: 683–726.

[5] Grotjahn Richard, Robert Black, Ruby Leung, Michael F. Wehner, Mathew Barlow, Mike Bosilovich, Alexander Gershunov, et al. (2016). North American extreme temperature events and related large scale meteorological patterns: a review of statistical methods, dynamics, modeling, and trends. Climate Dynamics, 46: 1151–1184.

[6] Qin Yue, Changyu Su, Dongdong Chu, Jicai Zhang & Jinbao Song (2023). A review of application of machine learning in storm surge problems. Journal of Marine Science and Engineering, 11(9): 1729.

[7] Hegde A. Aishwarya, Pruthviraj Umesh & Mohit P. Tahiliani (2024). Comparison of neural networks for binary spatial classification of rice field by studying temporal pattern using dual polarimetric SAR measurements. Journal of the Indian Society of Remote Sensing, Pages 1–19.

[8] Wu Yusi, Shumin Chen, Weibiao Li, Rong Fang & Haoya Liu (2020). Relative vorticity is the major environmental factor controlling tropical cyclone intensification over the Western North Pacific. Atmospheric Research, 237: 104874.

[9] Jordan Philipp & Peter Fröhle (2022). Bridging the gap between coastal engineering and nature conservation? A review of coastal ecosystems as nature-based solutions for coastal protection. J. of Coastal Conservation, 26(2): 4.

[10] Lai Guokun, Wei-Cheng Chang, Yiming Yang & Hanxiao Liu (2018). Modeling long-and short-term temporal patterns with deep neural networks. In the 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, Pages 95–104.

[11] Salacup, J.M., Farmer, J.R., Herbert, T.D., & Prell, W.L. (2019). Alkenone paleothermometry in coastal settings: evaluating the potential for highly resolved time series of sea surface temperature. Paleoceanography and Paleoclimatology, 34(2): 164–181.

Asian Journal of Applied Science and Technology (AJAST)
Volume 9, Issue 1, Pages 49-63, January-March 2025

[12] Deshmukh Kalyani H., & Gajendra R. Bamnote (2014). Natural disaster prediction optimized light gradient boosting enabled hybrid convolutional neural network and bidirectional long short-term memory. Intelligent Decision Technologies, 18724981241296365.

[13] Zhang Peng, Yunxia Zhang, Yang Wang, Yi Ding, Yizhou Yin, Zhen Dong & Xihong Wu (2024). Analysis of temporal-spatial patterns and impact factors of typhoon disaster losses in China from 1978 to 2020. Trop. Geogr., 44: 1047–1063.

[14] Kaur Harsurinder, Husanbir Singh Pannu & Avleen Kaur Malhi (2019). A systematic review on imbalanced data challenges in machine learning: Applications and solutions. ACM Computing Surveys, 52(4): 1–36.

[15] Amiri Zahra, Arash Heidari &Nima Jafari Navimipour (2024). Comprehensive survey of artificial intelligence techniques and strategies for climate change mitigation. Energy, 132827.

[16] Nandan Prasad Aditya (2024). Data Quality and Preprocessing. In Introduction to Data Governance for Machine Learning Systems: Fundamental Principles, Critical Practices, and Future Trends, Pages 109–223, Berkeley, CA: Press.

[17] Nabi Mattia Tun, Sara Ali, Zahid Mahmood, Muhammad Attique Khan & Shrooq Alsenan (2024). A self-supervised deep-driven model for automatic weather classification from remote sensing images. International Journal of Remote Sensing, Pages 1–26.

[18] Sathyanarayanan, S., & Roopashri Tantri, B. (2024). Confusion matrix-based performance evaluation metrics. Afr. J. Biomed. Res., 27(4): 4023–4031.

[19] Tao Chengchen, Zhizu Wang, Yilun Tian, Yaoyao Han, Keke Wang, Qiang Li & Juncheng Zuo (2024). Calibration of Typhoon Track Forecasts Based on Deep Learning Methods. Atmosphere, 15(9): 1125.

[20] Huang Kai-Bin, Tian-Shyug Lee, Jonathan Lee, Jy-Ping Wu, Leemen Lee & Hsiu-Mei Lee (2024). Applying Multi-Task Deep Learning Methods in Electricity Load Forecasting Using Meteorological Factors. Mathematics, 12(20): 3295.

[21] Battaglia Alessandro, Pavlos Kollias, Ranvir Dhillon, Richard Roy, Simone Tanelli, Katia Lamer, Mircea Grecu et al. (2020). Spaceborne cloud and precipitation radars: Status, challenges, and ways forward. Reviews of Geophysics, 58(3): e2019RG000686.

[22] Sundaresan, S., Surendar, M., Ananthkumar, T., Sureshkumar, K., & Jefrin, S.P. (2023). Impact of wind farms on surveillance radar system: a realistic scenario in Palakkad gap region. Journal of Ambient Intelligence and Humanized Computing, 14(6): 7949–7956.

[23] Mawatwal Manish Kumar & Saurabh Das (2024). An end-to-end deep learning framework for cyclone intensity estimation in North Indian Ocean region using satellite imagery. Journal of the Indian Society of Remote Sensing, 52(10): 2165–2175.

[24] Suresh Kumar, K., & Helen Sulochana, C. (2022). Local search five-element cycle optimized reLU-BiLSTM for multilingual aspect-based text classification. Concurrency and Computation: Practice and Experience, 34(28): e7374.

[25] Haji-Aghajany Saeid, Witold Rohm, Piotr Lipinski & Maciej Kryza (2024). Beyond the horizon: a critical analysis of AI-based weather forecasting models. Authorea Preprints.

[26] Khan Saad Mazhar, Imran Shafi, Wasi Haider Butt, Isabel de la Torre Diez, Miguel Angel López Flores, Juan Castanedo Galán & Imran Ashraf (2023). A systematic review of disaster management systems: approaches, challenges, and future directions. Land, 12(8): 1514.