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Tri-Modal Deep Learning Forecasting Framework to Enhance Performance of Tropical Cyclone Forecasting

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Abstract

Even with these advances, the complex nature of climatic processes in the atmosphere, sparse observation coverage, diverse data sources, and the dynamic nature of tropical cyclones (TCs) remain a challenge to predicting TC tracks and intensity. The existing deep learning approaches primarily rely on unimodal or bimodal observations, and frequently assume full observation or fully synchronized input, which are not always applicable and robust to observation deficient and data-scarce settings. The present work suggests a novel approach of taking a multi-modal generative deep learning approach to jointly predict the track and intensity of TCs using satellite imagery, atmospheric meteorological variables and historical cyclone track sequences. The results are hypothesized to be learnt by using an Improved Vision Transformer for spatial and structural information and historical cyclone trajectories and reanalysis variables for temporal and atmospheric information. Generative models will be discussed for reconstructing missing modalities and information when it is corrupted to enable forecasting when information is missing. The relationships between the three modalities will then be learned with a cross-attention-based fusion mechanism and physics-informed constraints will be added to enhance the physical consistency of forecasts. The proposed framework will also at the same time estimate the future parameters of cyclones like central pressure and maximum sustained wind. Its usefulness will be evaluated against well-available tropical cyclone track and intensity data from various basins by the errors in track and intensity, and the ability to reconstruct the cyclones, as well as by comparative experiments with available deep learning and multimodal track and intensity forecasting models. The aim is to produce a reliable and generally applicable forecasting framework that would maintain good forecasting skills when meteorological data is limited or not available.

Keywords: Missing Modality Reconstruction, Tropical Cyclone Forecasting, Tri-Modal Learning, Multimodal Data Fusion, Track Prediction, Intensity Prediction

1. Introduction

Tropical cyclones (TCs) are one of the most catastrophic natural hazards, leading to loss of life and damage to infrastructure, as well as severe socioeconomic impacts, especially in coastal and climate-sensitive areas. Accurate prediction of cyclone track and intensity with the associated hazards like rainfall and storm surge, is important for effective disaster preparedness and risk mitigation. Traditionally, cyclone prediction has been done using Numerical Weather Prediction (NWP) models, but they are very costly, and their prediction capability declines with increasing lead time. The use of Artificial Intelligence (AI) and Deep Learning has demonstrated promising capabilities recently to learn complex nonlinear relationships from massive meteorological data for cyclone forecasting. Hence, developing intelligent forecasting systems is a significant research field that can enhance the accuracy, reliability, and timeliness of the tropical cyclone forecasts.

Timely and accurate forecasting of cyclone intensity holds paramount importance in mitigating economic losses and minimizing human casualties [9]. The difficulty of predicting TC intensity is mainly due to our limited understanding of the complex physical processes and various factors related to TC intensification and decay [14]. At present, the numerical model is still the dominant way to forecast TC, and its ability mainly depends on the parameterization of physical processes within TCs. However, the performance of TC prediction is restricted by the complex dynamical mechanisms and the diverse influence factors, and still needs to be improved [16]. Many factors, such as the complex and chaotic energy exchange process between the sea and the atmosphere, and the imperfection of real-time data collection, may influence the prediction of TCs' intensity change. These rapid intensification processes are challenging to explain, and therefore, neither numerical nor statistical-dynamic models can predict

TC intensity changes accurately. A vital weakness for numerical methods is insufficient representation of the complicated dynamical process; however, increasing the number of variables or equations would exponentially demand computation. On the other hand, statistical methods, usually based on regression and lower computational costs, may not be effective in capturing nonlinear relationships. Therefore, their forecast results need to be further improved [22] [18]. These statistical models can also help the government departments to develop an appropriate strategy for disaster management and mitigation measures. In order to develop a model for predicting the TC activity, it is essential to know the contributing factors that affect TC intensity at basin- and regional-scale [19].

In recent years, many researchers have begun to apply DL algorithms to the forecasting of TC intensity [20]. DL has seen widespread success in domains such as computer vision, time series forecasting, and a variety of interdisciplinary applications. Leveraging the growing availability of diverse meteorological datasets, deep learning models, especially Recurrent Neural Networks (RNNs), offer strong potential for advancing TC prediction. The foundation of applying DL technology in specific research areas lies in the availability of high-quality datasets [21]. Popular neural network structures like Transformer and Long Short Term Memory (LSTM), based on historical time series information to predict future intensity. However, these simple time series features are still not sufficient to fully represent the current state of the TC, so the forecasting performance is not ideal. More researchers have been trying to use multimodal data, such as the renowned fifth generation of ECMWF reanalysis data (ERA5), to effectively extract the spatial features of the TC. This led to decent progress in short-term 24-hour (24h) forecasting. However, these methods generally suffer from significant error accumulation problems, resulting in poorer long-term forecasting performance [20].

2. Overview of Current Forecasting Approaches

A. Spatio-temporal and Transformer-Based Models

The purpose of work by Sattar et al. (2025) [1] was to increase the predictive ability of TCs with Spatio-Temporal Deep Learning (STDL) that is able to learn the patio-temporal evolution of TCs. It was able to successfully capture the temporal dependency of cyclone and their movement which led to improve the accuracy and consistency of cyclone forecasting in different cyclone datasets for proposed model. The main method applied to the framework, however, only incorporated one modal data type, and did not incorporate using satellite imagery or the atmosphere and reanalysis data, hence the capacity to incorporate complex interaction between the atmosphere and surface data would be limited. The attention-based data fusion (which needs further studies) and several data modalities to be integrated in the forecasting can be integrated to make forecasting more robust and accurate.

To overcome these drawbacks, Mulia et al. (2025) [2] introduced a Temporal Fusion Transformer (TFT) to model the temporal dependencies at long time horizons and to deliver interpretable probabilistic forecasts for tropical cyclones. High accuracy and scalability were achieved in this architecture, which highlights the most important temporal features, by using transformer-based architecture with attention mechanisms and variable selection networks. The model was however hard to implement and was not able to handle multimodal data fusion and lacking observations in real-time. Further studies are required to develop light-weight architectures for processing and modelling the meteorological data to handle the heterogeneous and incomplete data set.

B. Multimodal and Causal Learning Approaches:

To solve this, Zhang et al. (2025) [3] proposed the Infrared-Guided Multimodal Fusion (IRGMF) scheme to fuse the meteorological information and infrared satellite imagery in tropical cyclone forecasting. Application of the suggested procedure in this work resulted in noise reduction, a better presentation of features and reduced computational efforts for forecasting the accuracy. The framework was adopted, but assumed to be run with all the satellite observations and was not planned to be used during real time operations. Future research, as well as the development of efficient multimodal forecasting models, should include the creation of approaches for reconstruction of missing satellite data based on AI.

To accurately forecast the intensity of cyclones, Qu et al. (2025) [4] suggested the Tropical Cyclone Intensity Forecasting Network (TIFNet) which is a deep learning-based network. The model may be able to learn the non-linear correlation between the historic cyclone data and different atmospheric variables, with a lesser computational complexity cyclone intensity prediction.

The system could, however, only predict the intensity of the cyclone and could not predict the cyclone track and other hazards like rainfall and storm surge. Future study should focus on development of more integrated forecasting system, which can predict up to various features of cyclones.

To better understand the temporal dependence in the data for long-term forecasting of tropical cyclones, Liu et al. (2026) [5] introduced a Multi-Source Multiscale Constrained Auto Regressive (MSCAR) model that leverages the multiple data sources to model multiscale temporal dependence in the data. The architecture of the autoregressive system was found to be appropriate and it was used to obtain good performance results in the long-term prediction, delivering temporal evolution on a number of scales. However, due to the recursive prediction of autoregressive prediction, prediction errors were accumulated across long prediction time. Adaptive attention mechanisms and error correction strategies may be helpful for future studies to enhance long term forecasts.

In this study, Sahu et al. (2025) [29] have evaluated the capabilities of four cutting-edge global machine learning-based weather prediction models, namely, GraphCast, Pangu-Weather, Aurora and FourCastNet, for predicting the track, intensity and structure of tropical cyclones over different ocean basins. These AI models have been assessed for their performance in terms of track error, wind speed and thermodynamic characteristics and compared with the existing in-service Numerical Weather Prediction (NWP) models. The AI models were able to predict cyclone tracks with good accuracy; it was also observed that they were not too computation intensive but they were found to underestimate cyclones, which was attributed to bias in the training data and the lack of physical processes in the model. The authors suggested future research by means of physics informed hybrid AI in the field of TC intensity forecasting, combining machine learning and numerical weather prediction (NWP). The authors emphasized the need for future studies on hybrid AI model of physics-informed machine learning for enhancing the intensity forecasts of TCs.

Singh et al. (2025) [30] overviewed the recent developments in tropical cyclone forecasting methods, such as numerical weather prediction, machine learning and deep learning, tracking algorithms, and innovative AI-based solutions. The study pointed out that while there are a number of challenges, such as limited data availability, computational complexity, and the lack of physical interpretability, there are also a number of advances, including the use of transformer-based models, multimodal learning, and forecasting with AI. During the review it was discovered that there is still no common model for assimilation of multi-source meteorological data and physical understanding and no forecasting system is ready for this. The authors have called for future investigations of physics-informed, multi-modal and generative AI approaches to gain confidence and robustness in the forecast of tropical cyclones.

C. Intensity-Focused Forecasting Models:

For further improvement of the forecasting of the cyclone intensity, Li et al. (2025) [6] proposed an architecture, named Tropical Cyclone Intensity Kolmogorov–Arnold Network (TCIKAN), which is more interpretable using Kolmogorov–Arnold Networks (KANs). The model was successful in capturing the non-linear relationships, was simple to calculate and provided automatic selection of important predictors that was superior to some operational forecasting models. It was not linked to some of the physical processes in the atmosphere which are crucial for cyclone development like ocean–atmosphere interaction and wind shear. Future studies indicate that for complicated situations, deep learning technologies can be combined with the current knowledge (physical meteorological models) to improve the accuracy of the forecasts.

Due to the constraints of spatial and temporal dependencies, Jung et al. (2025) [7] suggested a CNN-LSTM hybrid network model that has bidirectional self-attention mechanism for more accurate prediction of tropical cyclone intensity. The spatial-temporal patterns corresponding to the meteorological data were captured by using the CNN, while the long-term temporal relationship was captured by using the LSTM and attention mechanism to decrease the prediction error and improve the operational analysis. The framework, however, was data dependent and needed extra inputs from the ocean and atmosphere, and was not applicable in data poor areas. Future studies will focus on a development of a multimodal model being able to keep prediction accuracy when there are incomplete observations.

To address the challenge, Wang et al. (2025) [9] created a stable model in the latent space that they referred to

as "Vector Quantized Long-Term Intensity (VQLTI)" to improve long-range tropical cyclone intensity estimation. It was demonstrated that the ability to reproduce intensity changes (which is generally nonlinear) can be obtained by using vector quantization (VC) and VC can be used to get better forecasting performance for longer time periods. But the structure proved to be quite difficult to implement the vector quantization; and with very dynamic seasons, it was not very accurate. More research would enable the model to be developed into a more efficient and flexible model to other environmental conditions.

To improve the forecasting process of intensity of tropical cyclones from satellite images in the North Indian Ocean, Sharma et al. (2025) [31] developed an improved framework based on deep learning technique which consists of a Vision Transformer (ViT), a Convolutional Block Attention Module (CBAM), and a ResNet. In the hybrid, it could learn the global features of visual contents and local features efficiently and the forecasting accuracy than the traditional CNN based approach. The framework was mostly adopted from the satellite picture with no attempt to integrate the other multimodal data sets and the atmospheric reanalysis and cyclone track data that could support the other multimodal data. Future research involves an attempt to develop the comprehensive cyclone forecasting of the fusion of visual data, atmosphere data and historical data through the tri modal fusion process.

Considering the North Indian Ocean region, deep learning based tropical cyclone intensity estimation and classification model using satellite image data was developed by Manju et al. (2025) [32] using ConvLSTM model. Based on observation, ConvLSTM could learn more information about the spatiotemporal evolution of cyclone than the traditional convolution layer, which resulted in better intensity estimation of the cyclone and cyclone classification. The model 2 used however did not have any other environmental parameter other than the satellite images and there was no inclusion of historical cyclone data and re-analysis data. The authors suggested novel enhanced attention mechanisms and integration of multiple meteorological data sources that will further enhance the accuracy of the forecast, and will be applicable during practice.

D. Attention-Based Architectures:

For predicting tropical cyclone intensity, Jiang et al. (2023) [24] made a modification of DMANet by combining deep attention mechanisms with sequential state estimation, which is called DMANet integrated with a Kalman Filter (DMANet_KF). The Kalman Filter was able to better smooth out the temporal noise and stabilize the intensity forecasting and it was possible to make a better prediction of the intensity. The framework, however, primarily focused on cyclone intensity but was not used concurrently to predict cyclone track which is an important component of a comprehensive cyclone forecast. The model is to be extended to make simultaneous predictions of cyclone track and intensity by joint model in future studies.

Xu et al. (2022) [25] developed a spatio-temporal dependency model – Attention Mechanism-based Convolutional Gated Recurrent Unit (AM-ConvGRU) for trajectory prediction. The attention mechanism enabled the model to be focused on the most informative spatial regions, and ConvGRU learned the temporal evolution, resulting in improved trajectory prediction and the maintenance of the local spatial structures. But the structure of this framework was originally for trajectory prediction and not specifically for cyclone structural evolution and intensification. Multimodal data having physical atmospheric information should be considered to predict the track and intensity of a cyclone in the future research with high accuracy.

To enhance the ability of deep learning models based on attention mechanism to predict rapid intensification of tropical cyclones in the North Indian Ocean, Sharma et al. (2025) [33] tried to improve the prediction. It employed state-of-the-art attention mechanisms to identify the most important meteorological features to influence cyclone intensification, resulting in enhanced cyclone prediction over traditional deep learning models. The framework, however, was mostly geared towards rapid intensification forecasting and did not at the same time estimate cyclone track or rely on multimodal data sources, such as satellite observations and atmospheric reanalysis. The authors suggested the extension of the framework to include a series of data sources and end-to end forecasting models to achieve comprehensive tropical cyclone predictions.

3. Methodology

A. Unimodal Deep Learning Models

Recently, deep learning (DL), which has been applied to various fields such as pattern recognition and image processing, has emerged as a promising alternative to the traditional numerical and statistical methods in TC trajectory prediction. DL models can overcome the limitation of involving explicit physical equations to model the complex nonlinear spatiotemporal pattern in large-scale geophysical data. The unimodal models that are being developed are based on a single meteorological modality (satellite data, radar data, reanalysis, etc.) and predict the future meteorological state from a single modality.

These models can be mathematically represented as:

$$\boldsymbol{Y_t = f(X_{t-n:t})}$$

where $\boldsymbol{Y_t}$ represents the forecasted weather output at time **t,** $\boldsymbol{X_{t-n:t}}$ denotes historical meteorological observations and f(·) denotes deep learning architectures such as CNN, LSTM or ConvLSTM. The ConvLSTM and hybrid convolutional networks have recently been used to capture spatio-temporal relationships in the atmosphere for precipitation nowcasting and track prediction of tropical cyclones [25, 26].

However, unimodal models are not enough to model the interaction between atmosphere and other media of the environment, and reduce robustness and generalization in terms of the rapidly changing extreme weather. [27].

B. Multimodal Fusion Approaches:

Multimodal fusion aims to integrate several different modalities to increase the robustness of the forecast, its predictive accuracy and the representation of the atmosphere in the learning process, such as satellite imagery, radar observations, oceanographic parameters, atmospheric re-analysis, etc. and sensor measurements. The inter-modal dependencies are captured in the following models: feature-level fusion, cross-attention learning, auto-encoder architectures and transformer-based multimodal representations.

If we have an input data that includes satellite imagery S, radar observations R, and atmospheric reanalysis datasets A, the mathematical formulation of multimodal fusion is expressed as:

$$\boldsymbol{F = \emptyset\,(S, R, A)}$$

where **F** denotes the final meteorological forecasting output generated by the multimodal framework**, φ (·)** represents the multimodal fusion operator.

C. Generative AI-Based Forecasting:

Generative Artificial Intelligence (AI) models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs) and diffusion-based architectures have proven to be effective strategies as promising way of meteorological data synthesis and extreme weather forecasting. These frameworks help immensely in reconstructing the atmosphere in the field, in generating a synthetic atmosphere and in the performance of medium range weather forecasting in sparse observation environments [30] and [31].

The optimum mathematical solution to the optimization problem of GAN is:

$$\boldsymbol{\min_{G}\max_{D} V\,(D, G)}$$

where G and D denote generator and discriminator networks, respectively.

The spatial realism of tropical cyclone forecasting models based on diffusion is enhanced and the intensity forecast errors are smaller than the deterministic deep learning methods. Synthetic data augmentation has also been shown to be useful to solve data imbalance and sparse sensing problems by using generative methods.

However, most of the current generative models are still geared towards data reconstruction and short-range forecasting, and they do not feature a significant amount of end-to-end forecasting pipelines.

D. Hybrid Physics–AI Models:

Hybrid physics-AI frameworks are derived from deep learning architectures with physical constraints of the atmosphere and numerical weather prediction systems, to enhance reliability and interpretability of forecasts. In neural learning frameworks, a number of physically inconsistent predictions are reduced by using these models which are derived from conservation laws and dynamical relationships in the atmosphere based on physical priors.

The process of forecasting is shown as:

$$\boldsymbol{Y = f_{AI}(X) + f_{Physics}\,(X)}$$

where $\boldsymbol{f_{AI}}$ denotes the neural forecasting component and incorporates atmospheric governing equations and physical $\boldsymbol{f_{Physics}}$ constraints.

The studies that have recently been conducted showed an improvement in the accuracy of the medium-range forecasts by the hybrid physics-AI systems relative to the purely statistical systems, both in terms of the medium-range trajectory of the tropical cyclones and in terms of consistency of the atmosphere states (measured by consistency) [32].

The application of the hybrid approach in general requires a large number of training examples, high-resolution simulations and a considerable amount of computational power to be implemented, while its implementation is also expensive, and therefore, the hybrid approach is not easily scalable and applicable in practice.

E. Data-Scarce Region Forecasting:

The regions with few observations (which are not complete) and without historical data are still a great challenge for forecasting. The existing methods to enhance the predictive ability in limited data include: Transfer learning, Synthetic data generation, Domain adaptation, and Multimodal fusion.

The transfer learning and domain adaptation are mathematically defined as:

$$\boldsymbol{\theta_t} + \boldsymbol{\theta_s} = \Delta\boldsymbol{\theta}$$

where $\boldsymbol{\theta_t}$ and $\boldsymbol{\theta_s}$ denote source-domain and target-domain model parameters, respectively.

In the atmosphere, generative diffusion models and GAN models have been shown to be effective for missing observations and resolving class imbalance problems in the atmosphere of rare extreme events [28]. The recent studies have shown that AI forecasting models can predict future scenarios once it has been installed, and that relying on AI can make a much more efficient prediction with much less computational load, in relevant areas and resource poor climate constraint regions, than using a conventional numerical technique [33].

The majority of forecasting models that are available, however, are trained and validated, and most of the data is rich data, making it difficult to be generalized to the heterogeneous climatic environment.

4. Proposed Approach

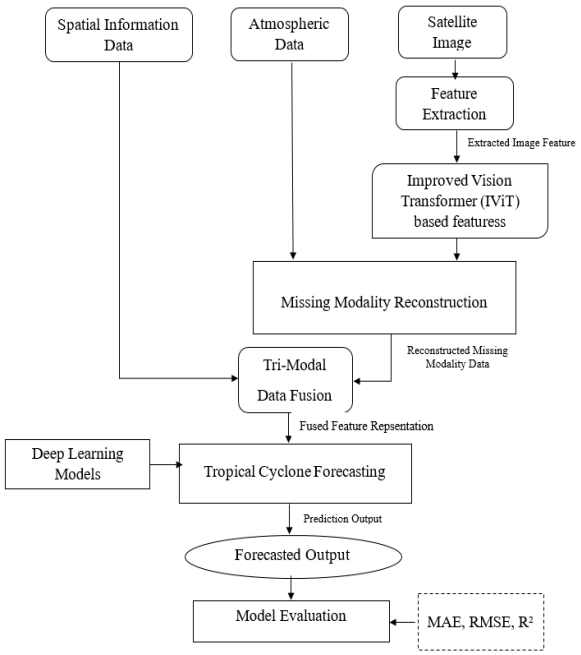


Fig. 1 Generalized Block diagram of the research work

The framework integrates three complementary data modalities, namely satellite imagery, meteorological variables, and historical cyclone sequences, to capture the spatial, atmospheric, and temporal characteristics of tropical cyclones. The overall framework is composed of following components, namely feature extraction, generative reconstruction, tri-modal data fusion, and performance evaluation.

A. Feature Extraction:

The first is the spatial information data which includes historical cyclone information like position, latitude, longitude, direction of movement, historical trajectory information from IBTrACS, JTWC, IMD, HURDAT2 etc. data, known as translation speed of cyclones. The following are a series of snapshots of the cyclone motion as a function of time.

The second one is atmospheric data which are the atmospheric conditions conducive to the formation and intensification of cyclones. The variables in the reanalysis data set are sea surface temperature, mean sea level pressure, vertical wind shear, relative humidity, geopotential height, air temperature, vorticity, divergence and ocean heat content, obtained from reanalysis datasets such as ERA5 or MERRA-2.

The third type are the satellite images obtained from the satellites such as INSAT-3D, INSAT-3DR, Himawari-8, GOES or Meteosat. Satellite imagery can also provide

valuable visual information on the organization of the clouds, a spiral rain band, eyewall structure and eye formation. Visual representations are then learnt from initial feature extraction using an Improved Vision Transformer (IViT). The Vision Transformer model is an alternative to the traditional CNN models which are able to learn long-range relations between image patches and which also yields good performance in the case of global structures in the cloud. This capability will aid distinguishing features associated with tropical cyclone rapid intensification and structural change.

B. Generative Reconstruction Module:

The novelty part of the proposed framework is that the modality reconstruction block does not exist. There may be missing modalities due to lack of observations or sensor limitations with practical forecasting scenarios. Such samples are not thrown away but instead the modality that is missing is filled in with information from the remaining modalities. There are a number of generative models that could be used for this purpose: Variational Autoencoders, Conditional Variational Autoencoders, Conditional Generative Adversarial Networks, Diffusion Models and Masked Autoencoders. This reconstruction process will be helpful in taking advantage of lack of data and will generate more robustness of the forecasting system.

C. Tri-Modal Data Fusion:

Feature extraction and reconstruction are applied then followed by a tri-modal fusion mechanism for the combination of the features from the three modalities. The aim of this stage is to get to know the complementary relationship and interactions between spatial, atmospheric and visual properties. There are a variety of fusion strategies used, such as early fusion, late fusion, attention based fusion and cross-attention fusion. The nice thing about this is that this cross-attention can also be dynamically learned by the model, as well as explicitly learned inter-modal relationships. This will lead to a more precise forecast and help in the interpretation of the forecasting system.

D. Forecasting Model:

The track prediction will predict the future location of the cyclone in latitude and longitude coordinates at the forecast times and the intensity prediction will estimate the cyclone related parameters such as maximum sustained wind and central air pressure. Forecasting can be done with any of the above LSTM models, Temporal Transformers, Sequence-to-Sequence models or fully connected prediction networks.

E. Evaluation and Comparison:

After forecasting, an evaluation and comparison stage is included to gauge the effectiveness of the proposed approach. The predicted values are compared with the true values (which are known from the benchmark datasets). The mean absolute error, root mean square error and coefficient of determination, R^2 are used to measure the performance of model.

5. Research Gaps

While deep learning has made significant strides in the prediction of tropical cyclones, there are still some key issues that have not been addressed. The current studies are largely based on datasets from a single modality (satellite or reanalysis) or limited multimodality (satellite or reanalysis) and are not sufficiently able to reflect the interactions between the atmosphere, ocean and cyclone dynamics. Thus, the complementary information available from the satellite imagery, atmospheric parameters and spatial cyclone information is not utilized fully, reducing the accuracy and robustness of the forecasting models ([5] - [6] - [9]). Furthermore, the current multimodal approaches usually assume that all the modalities are provided and of good quality. In-observations or corruption of satellite observations can also result from contamination by clouds and failure of the sensor, from errors or missing observations in the satellite data transmission. It is not a reliable and applicable model in any real world applications due to unavailable effective missing modality reconstruction method in [5] and [6] and [9].

The other significant constraint is that most deep-learning models are data-only, and there is no clear physical knowledge of the atmosphere, such as the atmospheric circulation, pressure systems, wind, thermodynamic constraints, etc. As a consequence, the predictions made may not be physically consistent all the time, especially during the changing situation of cyclones and at extremes ([8], [9], [20]). Moreover, many of the existing methods are only suitable for prediction of cyclone track or cyclone intensity exclusively, thus making it necessary to develop different models for the two different forecasting tasks. This separation of these approaches is not optimal in exploiting the natural relationship between trajectory and intensity change of a cyclone, and increases the

number of variables that has to be computed. A unified end-to-end forecasting framework is also required which incorporates multimodal data, infills missing modalities, uses physical meteorological knowledge and makes simultaneous track and intensity forecasts of tropical cyclones. Addressing these research gaps (as stated in [4], [24] and [25]) motivates and underlies the proposed research, which aims at creating a powerful, accurate and physically consistent framework for tropical cyclone forecasting.

6. Issues and Challenges

Major issues related to tropical cyclone prediction in areas with limited data are limiting the performance of both traditional numerical weather prediction (NWP) models and modern AI-based approaches. The primary issue is the lack and quality of observational data, especially over oceanic and developing areas, where satellite coverage may be sparse, and real-time measurements such as buoys and weather stations are few. This results in incomplete or noisy datasets which in turn affects the training and predictive accuracy of the model.

Another major challenge is the heterogeneity and imbalance of the available data sources, e.g., satellite images, reanalysis datasets, and historical cyclone records. Typically, these datasets differ in spatial resolution, temporal frequency, and measurement conventions, making it difficult to effectively fuse and align the data. Furthermore, the performance of multimodal and deep learning models is degraded by the absence of modalities (e.g., unavailable radar or real-time atmospheric parameters).

However, the generalization ability of deep learning models over different ocean basins is limited by the small size of labeled datasets, which leads to poor transferability and overfitting to data-rich regions. Also extreme events like high-intensity hurricanes are rare in nature leading to class imbalance which biases models toward more frequent, lower-intensity cases.

From a modeling perspective, the lack of physical interpretability in AI-based approaches reduces trust and reliability in operational forecasting. This is compounded by the difficulty of incorporating physics-based constraints into data-driven models, particularly when data is sparse.

These issues collectively highlight the need for robust, data-efficient, and physically consistent frameworks capable of handling missing data, improving generalization, and enabling reliable hurricane forecasting in data-scarce environments.

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