Storm Track and Intensity Forecasting using a hybrid machine learning approach

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I. Introduction

Storms, including cyclones, hurricanes, and typhoons, pose significant threats due to their destructive winds and heavy rainfall, causing extensive damage to infrastructure, ecosystems, and human lives. Accurate prediction of storm paths and intensities is crucial for disaster preparedness and minimizing losses. Despite advances in meteorological science and computational modeling, accurately forecasting sudden changes in storm behavior, such as rapid intensification or unexpected weakening, remains challenging. Traditional numerical weather prediction (NWP) models integrate physical laws governing atmospheric conditions but struggle with uncertainties stemming from rapid weather variations, incomplete observations, and computational constraints.

This study proposes a hybrid approach integrating sequence-based deep learning (Long Short-Term Memory (LSTM) and Transformers) with gradient boosting techniques (XGBoost, LightGBM) for predicting storm tracks and intensities. Additionally, physics-informed constraints such as storm kinetic energy, Coriolis force, and land interaction effects are incorporated to enhance the physical consistency and interpretability of the models. By combining machine learning models with fundamental meteorological principles, this work aims to improve the reliability and accuracy of cyclone forecasts.

The main contributions of this study include: (1) the development of a multi-modal hybrid model combining deep learning and tree-based machine learning methods; (2) incorporation of physics-informed constraints to enhance model generalization and physical validity; and (3) rigorous evaluation of model performance using real-world cyclone datasets with robust metrics, including the Haversine distance for path prediction and Mean Absolute Error (MAE) for intensity estimation.

II. Literature Review

Traditionally, storm prediction heavily relied on physics-based numerical weather prediction (NWP) models, which simulate atmospheric conditions using physical principles like the Navier-Stokes equations. These models, including the Weather Research and Forecasting (WRF) model[1] and the European Centre for Medium Range Weather Forecasts (ECMWF), have proven effective in large-scale storm forecasts [2]. Statistical models are less computationally demanding compared to NWP models, making them suitable for rapid forecasting in resource-constrained environments.

While both physics-based and statistical models have contributed significantly to storm prediction, they address different aspects of the problem and have distinct strengths and weaknesses. The integration of machine learning (ML) and artificial intelligence (AI) has gained popularity as a promising direction, offering solutions to handle the non-linearities and high-dimensional nature of storm-related data.

A. *Machine Learning for Storm Prediction*

Early ML approaches, such as regression and decision tree models, used structured datasets of historical storm paths to predict future trajectories. Ensemble methods, including XGBoost and LightGBM, further enhanced prediction accuracy by combining multiple weak learners to improve generalization. For example, Farmanifard and Ashgar (2023) utilized LSTM networks to predict tropical cyclone trajectories, achieving higher accuracy compared to traditional statistical models [3]

B. *Hybrid Models Combining AI and Physics-Based Techniques*

Hybrid models could be a promising solution to bridge the gap between traditional physics-based models and purely data-driven machine learning (ML) techniques. These models leverage the strengths of both approaches by incorporating physics-informed features into ML frameworks, thus improving accuracy, interpretability, and generalizability in storm forecasting. Liu et al. (2024) proposed a hybrid

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framework combining ML-based Pangu model with physics-informed features to extend tropical cyclone (TC) forecasts to 2 weeks. Their results demonstrate that the proposed hybrid ML/physics-based modeling framework significantly improves TC track and intensity forecasts compared with the global deterministic NWP models and standalone executions of Pangu and the WRF model. [4].

III. METHODOLOGY

The proposed hybrid AI framework integrates deep learning for cyclone path prediction, gradient boosting and deep neural networks for intensity forecasting, and physics-informed constraints to enhance prediction accuracy and consistency.

A. Data Preparation and Validation

Storm data is divided into training (70%), validation (15%), and testing (15%) sets. Hyperparameters for all models are optimized using Bayesian optimization based on validation set performance, ensuring reproducibility.

B. Path and Intensity Prediction Models

Cyclone trajectories are predicted using recurrent neural networks (LSTM and Transformers) that model temporal dependencies. Input features include historical latitude (LAT), longitude (LON), wind speed (WMO_WIND), storm direction (STORM_DIR), and distance to land (DIST2LAND). Outputs are future LAT and LON coordinates. Storm intensity is forecasted using gradient boosting (XGBoost, LightGBM) and deep neural networks, predicting maximum wind speed (WMO_WIND) and minimum pressure (WMO_PRES). The model incorporates historical intensity metrics, atmospheric pressure, and storm classification attributes.

C. Hybrid Model with Physics-Informed Constraints

The outputs of individual path and intensity prediction models are integrated into a hybrid model. This integration weights the predictions based on their validation accuracy, producing unified and optimized forecasts. Physics-informed constraints are explicitly incorporated into the hybrid model's loss function, including:

- Wind-Pressure Relationship: Penalty enforcing empirical correlations between wind speed and atmospheric pressure.

$$L_{\text{physics}} = \gamma \sum_i \left(WMO\_WIND_i - f(WMO\_PRES_i) \right)^2 \qquad (1)$$

Where *f(.)* is the empirical wind-pressure function, and controls penalty strength.

- Storm Kinetics: Minimizing trajectory deviations from observed storm speed and direction.
- Land Interaction Effects: Regularizing intensity predictions based on distance to land, ensuring realistic weakening post-landfall.

XAI techniques, including SHapley Additive exPlanations (SHAP) are utilized to enhance the interpretability and transparency of the hybrid model. This module identifies influential features affecting predictions and validates model outputs.

Performance of the hybrid model is comprehensively assessed using standard metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2 Score, and Haversine Distance Error for path accuracy. The final hybrid model incorporates the best-performing path and intensity prediction models, selected through quantitative evaluation metrics and qualitative interpretability analysis facilitated by the XAI module.

IV. RESULTS AND DISCUSSION

The performance of different models for cyclone path and intensity prediction was evaluated using standard regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score. The Haversine Distance Error was used to measure geographic deviations in path prediction.

TABLE I. TRACK PREDICTION RESULTS

Model	MAE (LAT)	RMSE (LAT)	R^2 (LAT)	MAE (LON)	RMSE (LON)	R^2 (LON)
Linear Regression	0.7233	2.8345	0.9813	2.5856	14.358	0.9687
Decision Trees	0.6661	2.9978	0.9790	2.7185	15.009	0.9658
Random Forest	0.6072	2.7585	0.9823	2.4643	13.812	0.9710
XGBoost	0.1165	0.0711	0.9998	0.3174	16.643	0.9975
LightBGM	0.1069	0.0451	0.9999	0.3278	17.639	0.9973

These are partial results and will be updated as further experiments refine the model performances. The hybrid approach will integrate the best-performing models for each variable to optimize overall cyclone path and intensity prediction.

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