

## LITERATURE REVIEW

S.NO	AUTHOR	PAPER TITLE	YEAR	INPUT DATA	METHOD	MODEL (AI/ML)	RESULT
1.	Chong Wang, Nan Yang, Xiaofeng Li	Advancing forecasting capabilities: A contrastive learning model for forecasting tropical cyclone rapid intensification	2025	Satellite infrared imagery, atmospheric and oceanic data (U, V winds, potential vorticity, SST, historical forecast factors), ERA5 and IFS-Operational datasets (2000–2021 Northwest Pacific TCs)	Contrastive learning approach to handle sample imbalance; paired-sample voting mechanism; feature extraction of 3D environmental factors	RITCF-contrastive deep learning model	RI TC Probability of Detection (POD) 92.3%, False Alarm Rate (FAR) 8.9%; 3× reduction in false alarms compared to existing DL methods
2.	Zeyi Niu, Wei Huang, Hao Li, Xuliang Fan, Yuhua Yang, Mengqi Yang, Bo Qin	Machine Learning (ML)–Physics Fusion Model Outperforms Both Physics-Only and ML-Only Models in Typhoon Predictions	2025	2024 Western North Pacific typhoon cases; CMA best track data; ECMWF HRES; SHTM model outputs; FuXi ML forecasts; Fengyun-4B satellite brightness temperatures; SAR wind data	Hybrid ML–physics forecasting using spectral nudging of FuXi outputs into the SHTM physical model; resolution enhancement from 9 km to 3 km	FuXi–SHTM hybrid model	Reduced track forecast errors by 16.5% (72 h) and 5.2% (120 h); reduced intensity forecast errors by 59.7% and 47.6% vs FuXi; improved cloud and wind structure realism
3.	M.A. Fernandez, Elizabeth A. Barnes, Randal J. Barnes, Mark	Predicting Tropical Cyclone Track Forecast Errors using a	2025	NHC and CPHC official forecasts (2013–2023); environment	Neural network predicting parameters of a bivariate normal	Probabilistic neural network (dense layers, ReLU, softplus/tanh outputs)	Dynamic, well-calibrated uncertainty estimates outperform current NHC static

	DeMaria, Marie McGraw, Galina Chirokova, Lixin Lu	Probabilistic Neural Network		al predictors; dynamical model outputs (GFS, ECMWF, UKMet, HWRF); statistical-dynamical model predictors (D-SHIPS)	distribution for track uncertainty ; separate models per basin and lead time; leave-one-year-out training		methods; comparable to GEFS ensemble performance; negligible computational cost
4.	Keliang Wu, Bohan Zhao, Yujie Yang, Yumo Ouyang	Tropical Cyclone Trajectory Prediction with Integration of Shallow Convolutional Layer and Bi-LSTM	2025	HURDAT2 dataset (Atlantic basin, 1851–2020), processed sequences of 5 time steps	Integration of shallow 1D convolutional layer, Bi-LSTM, and LSTM; hyperparameter tuning with various optimizers, learning rates, and batch sizes	Conv-Bi-LSTM hybrid deep learning model	Proposed model outperformed basic RNN, LSTM, and GRU in MSE, MAE, RMSE; achieved MAE=0.0172, RMSE=0.0458 on test set
5.	Zhibo Ren, Pritthijit Nath, Pancham Shukla	Improving Tropical Cyclone Forecasting with Video Diffusion Models	2025	Infrared satellite imagery and ERA5 meteorological data, sequences of 10 consecutive frames	3D UNet-based video diffusion model with temporal convolutions and attention; two-stage training (single-frame then multi-frame)	Video diffusion model (VDM) with temporal layers	Outperformed baseline by 19.3% MAE reduction, 16.2% PSNR improvement, 36.1% SSIM improvement; extended reliable forecast horizon from 36h to 50h
6.	Mark DeMaria, James L. Franklin, Galina Chirokova, Jacob Radford,	Evaluation of Tropical Cyclone Track and Intensity Forecasts from Artificial	2024	NHC verification dataset for Northern Hemisphere TCs (May–Nov 2023), GFS	Evaluation of four open-source AIWP models (FourCastNetv1, FourCastN	FourCastNetv1, FourCastNetv2-small, GraphCast-operational, Pangu-Weather	Track forecast errors comparable to best operational models; intensity

	Robert DeMaria, Kate D. Musgrave, Imme Ebert-Uphoff	Intelligence Weather Prediction (AIWP) Models		initial conditions, ATCF archives	etv2-small, GraphCast-operation al, Pangu-Weather) using NHC verification metrics	(Fourier-based NN, Graph NN, etc.)	forecasts had substantial low bias; improved consensus track forecasts by up to 11%
7.	Chengchen Tao, Zhizu Wang, Yilun Tian, Yaoyao Han, Keke Wang, Qiang Li, Juncheng Zuo	Calibration of Typhoon Track Forecasts Based on Deep Learning Methods	2024	WRF model forecasts, CMA Best-Track data, ERA-Interim reanalysis, NCEP FNL dataset (2000–2022)	Correction of WRF-forecasted tracks using deep learning (BiLSTM + ConvLSTM + WDL / ConvGRU / xDeepFM); error decomposition	BiLSTM, ConvLSTM, WDL, ConvGRU, xDeepFM	Best model (BiLSTM + ConvLSTM + WDL) reduced 72h track prediction error by 37.6% (255.18 km to 159.23 km)
8.	Gabriele Accarino, Davide Donno, Francesco Immorlano, Donatello Elia, Giovanni Aloisio	An Ensemble Machine Learning Approach for Tropical Cyclone Localization and Tracking From ERA5 Reanalysis Data	2023	ERA5 reanalysis data (MSLP, wind gusts, vorticity, temperature), IBTrACS cyclone center records (1980–2019)	Ensemble of multiple ANN architectures with different hyperparameters; hybrid tracking scheme integrating ML detection with deterministic tracking	Artificial Neural Networks (ensemble approach)	Improved cyclone center localization over single models; 71.49% probability of detection, 23% false alarm rate over 40 years
9.	Fan Meng, Yichen Yao, Zhibin Wang, Shiqiu Peng, Danya Xu, Tao Song	Probabilistic forecasting of tropical cyclones intensity using machine learning model	2023	SHIPS predictors (1982–2017 reanalysis, 2010–2020 operational data), IBTrACS and Emanuel's	Hybrid LightGBM + NGBoost framework (TCP-NGBoost); Leave-One-Year-Out strategy;	LightGBM + NGBoost (probabilistic ML)	Outperformed state-of-the-art operational models in point forecasts; provided calibrated

				global TC dataset	feature selection from SHIPS dataset		probabilistic intervals; improved reliability for disaster warnings
10.	Jia Ren, Nan Xu, Yani Cui	Typhoon Track Prediction Based on Deep Learning	2022	NOAA best track data for South China Sea typhoons (1949–2021) + meteorological variables (wind speed, pressure, radius, etc.)	Data preprocessing (cubic spline interpolation for missing data), Granger causality feature selection, hybrid CNN–LSTM	C-LSTM	Outperformed LSTM baseline; reduced prediction error for South China Sea typhoon tracks