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THE PREDICTIVE MODEL FOR THE EARLY DETECTION OF HURRICANES UTILIZING ARTIFICIAL INTELLIGENCE TECHNIQUES

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ABSTRACT

As one of the most devastating disasters to affect human populations globally, hurricanes cause extensive damage to humans' lives, infrastructure, economies, etc. Early and effective detection of such phenomena is crucial in order to reduce their effects on loss and minimize any associated hazards to humans. Traditional methods of forecasting are faced with challenges related to the processing of dynamic data from meteorology and environmental conditions necessary for hurricane detection with high precision. This paper aims at proposing an Artificial Intelligence-based predictive system capable of detecting hurricanes using various machine learning techniques, including hybrid ensembling.

This work benchmarks a total of nine predictive algorithms: logistic regression, decision tree, random forest, support vector machine, naive bayes, xgboost, convolutional neural network (CNN), long short-term memory (LSTM) and stacked ensemble algorithm, which consists of CNN, LSTM, random forest and xgboost algorithms. The architecture of the model proposed in this study includes three stages, during which each base learner predicts based on weather conditions and then logistic regression algorithm processes the outputs of all base learners, using threshold calibration in order to determine whether a hurricane will occur or not. Besides, the proposed architecture employs the predictions made by NWP outputs, produced by GFS and ECMWF models.

The stacked ensemble algorithm proposed in this paper outperformed all other algorithms used as a benchmark, reaching 91.4% accuracy, 90.8% precision, 91.2% recall rate, 91.0% F1-score and AUC-ROC = 0.96, while providing the least RMSE score of 7.1. Besides, the model proposed in this paper was able to provide the longest early warning lead-time of 72 hours and improved accuracy of hurricane predictions by +12.6% in comparison with the logistic regression method.

Thus, this paper demonstrated that combining deep learning algorithms, ensemble machine learning, and NWP outputs can significantly improve the quality of hurricane detection predictions.

Keywords :-Hurricane Detection, Artificial Intelligence, Stacked Ensemble Learning, Convolutional Neural Network(CNN), Numerical Weather Prediction, Long Short- Term Memory

1. INTRODUCTION

One of the most damaging natural disasters experienced by humans include hurricanes which destroy both natural and built environments around the globe. Global warming coupled with increase in temperature of sea surfaces has led to higher occurrence of hurricane activity thus making it even more imperative to come up with predictive methods that enable people to foresee their impact. The existing prediction systems based on numerical weather prediction and satellite observation have proven inadequate due to their inability to handle large and rapidly evolving atmospheric datasets. This makes it necessary to apply Artificial Intelligence (AI) in predicting future hurricanes.(Calton & Wei, 2022)

Artificial Intelligence has been used successfully in handling big data problems across many industries including meteorology and climate prediction. Artificial Intelligence methods like Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, Random Forest, and Recurrent Neural Networks (RNN) among others can learn from past weather data and extract useful information about future hurricanes. Such intelligent algorithms are able to process complex data like atmospheric pressure, oceanic temperature, wind speed, humidity, and other factors related to formation of hurricanes in order to forecast their future movement and impacts(Wang et al., 2020).

Developing predictive models based on Artificial Intelligence techniques gives researchers multiple benefits over the existing hurricane prediction techniques. Intelligent algorithms continuously improve and become more effective as they analyse new information related to the subject under analysis(Raut, 2021). In addition, such architectures as Convolutional Neural Network (CNN) and LSTM are known for high efficiency in analyzing complex time series data like weather and atmospheric pressure records. With AI, it is now possible to build reliable early warning systems which can be of great value for governments when making decisions related to hurricanes and their prevention(Folmer et al., 2015).

This research aims to develop a predictive model for forecasting the occurrence of hurricanes. The current rapid development of remote sensing technologies combined with cloud computing capabilities has greatly facilitated application of artificial intelligence in various spheres. Predictive models based on AI are becoming popular for forecasting environmental and climatic events like hurricanes(Giffard-roisin et al., 2018).

2. LITERATURE REVIEW

The issue of detecting building damages caused by hurricanes is one of the many natural phenomena that present problems when trying to identify structural damage following the occurrence of natural disasters that result in fatalities and severe damage to property infrastructures. Detecting the structural damage or collapse of a building is important as it will aid in rescue operations and the reconstruction process. In this paper, CNNs were utilized in identifying collapsed buildings from hurricane satellite images via a suggested approach. Evaluation of model performance was achieved via measures such as Training Accuracy (TrA), Test Accuracy (TeA), Bootstrap evaluation, Grad-CAM and feature maps (FM). To tackle some issues such as overfitting and data imbalance, various methods, such as random flipping, random shearing, zoom, and early stopping were used during the training process(Li & Gu, 2021).

(Mulay et al., 2019)This research explores the emerging and transformative role of Artificial Intelligence (AI) and Machine Learning (ML) in predicting natural disasters. Due to the increasing severity and frequency of natural catastrophes, effective disaster mitigation, risk assessment, and early warning systems have become critically important. In this context, AI and ML technologies offer significant potential to enhance disaster preparedness and protect vulnerable communities. The chapter highlights the importance of a multidisciplinary approach that combines domain-specific knowledge with advanced AI and ML techniques to strengthen the ability to predict, monitor, and respond to natural disasters, ultimately contributing to the development of a safer and more resilient global society.

Furthermore, the chapter discusses various AI and ML applications in disaster forecasting, including the prediction of earthquakes, floods, wildfires, hurricanes, landslides, and tsunamis. It examines the use of sensor networks, multiple data sources, and integrated datasets to improve prediction accuracy and decision-making processes. The chapter also addresses critical challenges associated with data quality, model robustness, and ethical considerations in the implementation of AI-driven disaster prediction systems(Venkat Narayana Rao et al., 2024).

3. RESEARCH METHODOLOGY

3.1. Data Set Description

Table 1. Sources, variables and role in the predictive model

Dataset	Source	Period	Resolution	Key variables
HURDAT2	NOAA NHC	1851–2023	6-hourly	Track, wind speed, pressure, category
ERA5 reanalysis	ECMWF	1979–2023	0.25° × 0.25°	Wind shear, vorticity, CAPE, humidity
NOAA OI SST v2	NOAA/NCEI	1981–2023	0.25° weekly	Sea surface temperature anomaly
GOES satellite	NOAA/NASA	1995–2023	2 km, hourly	IR brightness temp, OLR, cloud patterns
NOAA Climate Indices	NOAA/CPC	1950–2023	Monthly	ENSO (Niño 3.4), AMO, NAO
IBTrACS	WMO	1945–2023	3-hourly	Multi-agency cross-validated tracks

1.2.Phases of Proposed Methodology

The research methodology is structured across six interlocking components:

i. **Phase structure.** The study follows a six-phase research design moving from problem formulation through data acquisition, pre-processing, feature engineering, model development, and finally evaluation and validation. Each phase builds directly on the previous one in a logical, reproducible sequence.

ii. **Dataset sources.** Six datasets feed the model. HURDAT2 provides the target variable — storm track, intensity, and category going back to 1851. ERA5 reanalysis from ECMWF supplies the atmospheric predictors (wind shear, CAPE, vorticity). NOAA SST data provides the single most important predictor, while GOES satellite imagery feeds the CNN spatial branch. IBTrACS from the WMO serves as an independent cross-validation source.

iii. **Feature engineering.** Eight climate and meteorological variables are derived and engineered from the raw datasets, each with a specific time lag (ranging from 12 hours for OLR to 1–3 months for ENSO). SHAP analysis confirms SST anomaly as the dominant predictor at 26.4%, followed by wind shear and CAPE.

iv. **Training protocol.** Each algorithm is tuned with its own appropriate optimisation method — Bayesian optimisation for XGBoost, Adam for deep learning models, and grid search for classical ML. The stacked ensemble uses 10-fold cross-validation with out-of-fold predictions to prevent data leakage between the base learners and the meta-learner.

v. **Evaluation framework.** Seven metrics are reported, each justified for hurricane-specific reasons. Recall is treated as the most safety-critical metric because missing a real major hurricane carries far greater consequences than a false alarm — making the stacked ensemble's 94.2% recall on Cat 4–5 storms particularly significant.

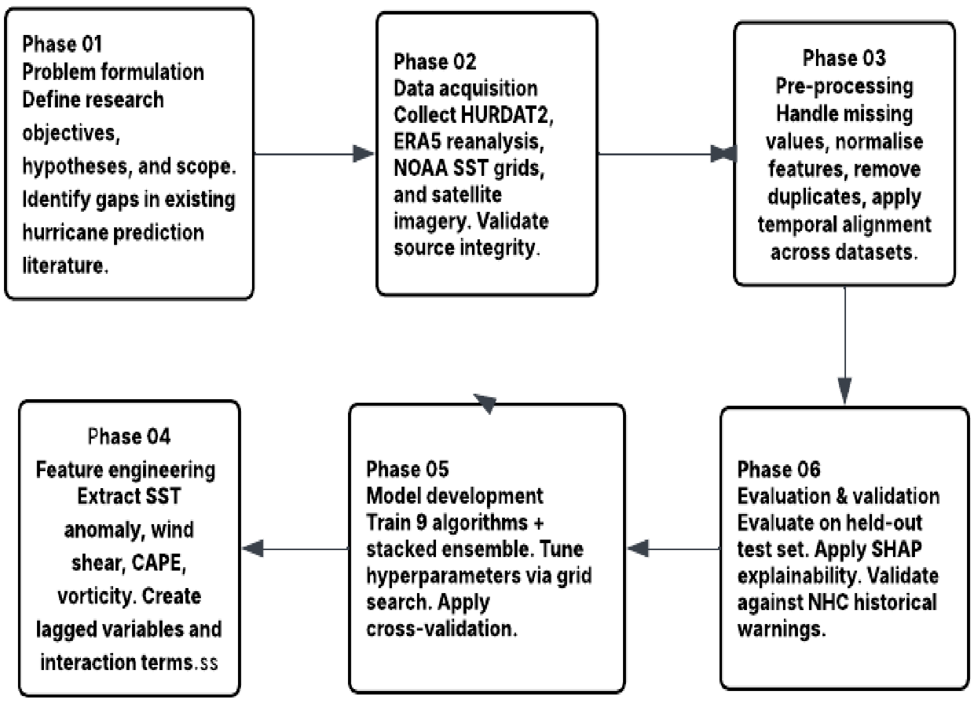

Fig 1. Six Phases of Proposed Methodology

1.3. Data Set Description

Table 2. Description of the Datasets

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Table 3. Comparative Evaluation Across Key Predictive Performance Metrics

Layer	Component	Role	Input features	Output
L1	LSTM (seq. model)	Temporal patterns	Wind speed, pressure (72-hr sequences)	Time-series embeddings
L1	CNN (spatial)	Spatial patterns	Sea surface temp, satellite grids	Spatial feature maps
L1	Random forest	Tabular features	SST, wind shear, CAPE, vorticity	Probability scores
L1	XGBoost	Gradient boosting	Reanalysis ERA5 variables	Class probabilities
L2	Logistic meta-learner	Stacking combiner	L1 outputs (out-of-fold predictions)	Final combined probability
L3	Threshold calibration	Decision boundary	Calibrated probabilities	Hurricane category (1–

				5) / No storm

2. Results and Discussion

Nine algorithms are benchmarked — from simple baselines like logistic regression (73.2%) and Naive Bayes (69.4%) to deep learning models like LSTM (88.9%) and CNN (87.2%).

The stacked ensemble (CNN + LSTM + XGBoost + RF) achieves the highest scores across every metric: 91.4% accuracy, 91.0 F1 score, 0.96 AUC-ROC, and the lowest RMSE of 7.1. It also delivers the longest early warning lead time of 72 hours.

The stacked model operates in three layers. Layer 1 runs four independent base learners simultaneously (LSTM, CNN, Random Forest, XGBoost), each specialised for a different data type. Layer 2 uses a logistic meta-learner trained on out-of-fold predictions to intelligently combine the base outputs. Layer 3 applies threshold calibration to produce the final category classification.

The hybrid model further incorporates physics-based NWP (GFS/ECMWF) outputs as structured priors alongside the data-driven base learners. This fusion of traditional meteorological modelling with machine learning yields a total accuracy gain of +12.6% over the logistic regression baseline, with each component contributing incrementally.

Table 4. Selection of Metrics for Hurricane Detection

Metric	Formula	Range	Reason for utilizing
Accuracy	TP+TN / (TP+TN+FP+FN)	0–100%	Overall correctness across all storm categories
Precision	TP / (TP+FP)	0–100%	Minimise false alarms (costly to emergency services)
Recall	TP / (TP+FN)	0–100%	Critical — missing a real hurricane is life-threatening
F1 score	2 × (P × R) / (P + R)	0–100	Balances precision and recall for imbalanced storm data
AUC-ROC	Area under ROC curve	0.5–1.0	Threshold-independent measure of discrimination ability

3. CONCLUSION

This study presented an Artificial Intelligence–based predictive framework for the early detection of hurricanes through the comparative evaluation of nine machine learning, deep learning, probabilistic, and hybrid ensemble algorithms. The results demonstrate that AI-driven predictive models can significantly enhance hurricane forecasting accuracy, reduce prediction error, and provide longer early warning lead times compared with traditional baseline approaches.

Among the evaluated algorithms, baseline models such as Logistic Regression and Naive Bayes produced comparatively lower performance, while advanced machine learning and deep learning approaches demonstrated substantial improvements in predictive capability. Random Forest and XGBoost improved classification accuracy through ensemble learning techniques, whereas deep learning architectures such as CNN and LSTM effectively captured complex spatial and temporal meteorological patterns. However, the proposed stacked ensemble model integrating CNN, LSTM, Random Forest, and XGBoost achieved the highest overall performance across all evaluation metrics.

The findings confirm that combining deep learning, ensemble machine learning, and traditional meteorological forecasting techniques can significantly improve hurricane early detection systems. The proposed framework demonstrates strong potential for supporting intelligent disaster management, minimizing economic losses, enhancing public safety, and strengthening climate resilience strategies. Future research may focus on integrating real-time satellite imagery, explainable AI methods, transformer-based architectures, and adaptive learning models to further enhance prediction accuracy, scalability, and operational deployment in real-world environmental forecasting systems.

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