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A Systematic Review on the Prediction of Hurricanes by Utilizing Machine Learning Techniques

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Abstract:

Hurricanes are powerful, large-scale tropical cyclones that form over warm ocean waters in the Atlantic Ocean and Eastern Pacific Ocean. These massive storm systems are characterized by their distinctive circular shape and intense wind speeds.

Objective: To conduct a comprehensive systematic review of artificial intelligence (AI) techniques for hurricane prediction, analysing the current state of technological innovations, methodological approaches, and predictive capabilities in meteorological forecasting.

Background: Hurricanes represent one of the most destructive natural phenomena, causing significant economic and humanitarian impacts globally. Traditional forecasting methods have limitations in accurately predicting hurricane trajectories, intensities, and potential impacts, necessitating advanced computational approaches.

Methodology: In this paper, a systematic review is conducted by following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Comprehensive searches were performed across multiple databases including Web of Science, Scopus, IEEE Xplore, and specialized meteorological research repositories.

Conclusion: Artificial intelligence techniques demonstrate transformative potential in hurricane prediction, offering unprecedented accuracy and insights. The integration of advanced computational methods with traditional meteorological approaches presents a promising frontier in natural disaster forecasting and mitigation strategies.

Keywords: Hurricane Prediction, Artificial Intelligence, Machine Learning, Meteorological Forecasting, Natural Disaster Management, Deep Learning, Predictive Modelling.

1. Introduction

The term "hurricane" traces its roots to Mayan culture, referring to their deity associated with lightning, wind, storms, and fire, depicted with one leg. While modern society views hurricanes primarily as destructive forces causing death and economic devastation, pre-Hispanic civilizations had a markedly different perspective. They recognized hurricanes as vital phenomena that delivered essential water resources to their lands. This historical view holds renewed relevance today, as both Mexico and the United States face significant drought conditions. Despite their destructive potential, hurricanes might paradoxically offer a natural solution to these water scarcity challenges, highlighting the complex relationship between these powerful storms and human society – both as a threat and a potential resource for addressing critical water needs.

Tropical hurricanes, which regularly devastate wildlife and communities across North and Central America, are now being studied through innovative machine-learning technology to improve prediction capabilities. A new research framework employs machine learning to deepen our understanding of how hurricanes interact with complex land, air, and ocean systems. Analysis of NOAA's hurricane classification data from 1950 to 2021, using wavelet analysis, revealed that Category 2-4 hurricanes typically form during the positive phase of a roughly five-year cycle. The study also found that the most severe hurricanes (Category 5) exclusively formed during the positive phase of a ten-year cycle. These patterns helped researchers categorize historical hurricane seasons into distinct periods of high activity and inactivity**.** Both natural and human-caused factors contribute to the varying levels of tropical cyclone activity. In the USA, Mexico, and Caribbean regions, these powerful storms - known as hurricanes - combine multiple destructive elements: powerful winds, heavy rainfall, storm surges, and intense wave activity. Each year, tropical and subtropical regions face severe storms of various intensities and origins. Given the significant damage these events cause to coastal communities and society at large, understanding how hurricanes form and intensify is crucial for developing effective early warning systems and preventive measures. Hurricanes are among the most destructive natural disasters, causing significant loss of life and property damage. Accurate prediction of hurricane behaviour is crucial for effective disaster management and mitigation strategies. In recent years, machine learning techniques have shown promising results in improving hurricane forecasting accuracy. This systematic review aims to synthesize current research on machine learning applications in hurricane prediction, evaluate their effectiveness, and identify areas for future research.

2. Theoretical Framework/Theory/Literature Review

A comprehensive literature search was conducted using databases such as Web of Science, Scopus, and IEEE Xplore. Keywords included "hurricane prediction," "machine learning," "artificial intelligence," and related terms. The search was limited to peer-reviewed articles published between 2010 and 2021. A comprehensive literature search was conducted using multiple academic databases to ensure broad coverage of relevant studies. The primary databases utilized were: 1. Web of Science: Known for its extensive coverage of high-impact, peer-reviewed journals across various scientific disciplines. 2. Scopus: Offering a wide range of peer-reviewed literature, including scientific journals, books, and conference proceedings. 3. IEEE Xplore: Specifically chosen for its focus on electrical engineering, computer science, and related fields, which are relevant to machine learning applications. The search terms were carefully selected to capture studies related to hurricane prediction using machine learning techniques. The primary keywords used in the search included: - "hurricane prediction", "machine learning", "artificial intelligence", "deep learning", "neural networks", "tropical cyclone forecasting", "storm track prediction", "hurricane intensity estimation"

Boolean operators (AND, OR) were used to combine these terms effectively. For example:("hurricane prediction" OR "tropical cyclone forecasting") AND ("machine learning" OR "artificial intelligence" OR "deep learning")

Additional search strategies included: 1. Reviewing reference lists of identified articles for relevant studies not captured in the initial database search. 2. Conducting forward citation searches on key papers to identify more recent studies building upon significant works. 3. Consulting with domain experts to identify any potentially missed important studies or ongoing research projects. 4. Exploring conference proceedings and preprint servers (e.g., arXiv) for cutting-edge research that may not yet be published in peer-reviewed journals. The search results were then screened based on predefined inclusion and exclusion criteria to ensure only relevant studies were included in the final review. This process involved reviewing titles and abstracts, followed by full-text assessment of potentially eligible studies.

3. Research Methodology/Experimental

3.1. Inclusion Criteria

The search strategy for the systematic review of hurricane prediction using machine learning techniques is comprehensive and well-structured. It covers multiple academic databases, including Web of Science, Scopus, and IEEE Xplore, which are appropriate for the topic. The selection of keywords and their combination using Boolean operators is thorough and likely to capture relevant studies. To enhance the search strategy, consider:

1. Expanding the database list to include subject-specific databases like AMS (American Meteorological Society) journals or NOAA's library catalog.

2. Including additional keywords such as "data mining," "predictive modeling," or specific algorithm names (e.g., "support vector machines," "random forests").

3. Considering grey literature sources like government reports or technical documents from meteorological organizations.

4. Implementing a snowballing technique by examining the reference lists of included studies and conducting forward citation searches.

5. Using controlled vocabulary or subject headings specific to each database to ensure comprehensive coverage.

6. Documenting the exact search strings used for each database to ensure reproducibility.

7. Considering the use of citation management software to organize and deduplicate search results efficiently.

The inclusion and exclusion criteria are clear and appropriate for the review's focus is considered through 1. Specifying a minimum sample size or study duration if applicable. 2. Clarifying whether studies using hybrid methods (combining traditional and machine learning approaches) are included. 3. Addressing how to handle studies with multiple publications on the same dataset. The data extraction and analysis process appear sound. To strengthen this section: 1. Develop a standardized data extraction form to ensure consistency across studies. 2. Consider using multiple reviewers for data extraction and implementing a process for resolving discrepancies. 3. Specify the approach for assessing the quality or risk of bias in included studies.

3.2. Research Questions

i. How do different machine learning algorithms compare in their effectiveness for predicting hurricane trajectories?

ii. What are the most accurate machine learning techniques for forecasting hurricane intensity?

iii. What are the current limitations and challenges in applying machine learning to hurricane forecasting?

4. Related Work

(Ho et al., 2024), Two artificial intelligence (AI) models were developed to identify the center of tropical cyclones (TCs) in the western North Pacific, utilizing six geostationary satellite channels: four infrared (IR) channels for brightness temperature, one shortwave IR channel, and one visible channel for reflectivity. (Wei and Yang, 2021) The first model is a convolutional neural network (CNN) for spatial data processing, while the second is a convolutional long short-term memory (LSTM) model designed to capture spatiotemporal features. These models were trained, validated, and tested using spatial images from the Himawari-8 satellite (2016–2021), with initial positions derived from the European Centre for Medium-Range Weather Forecasts' 6- or 12-hour predictions. Initial error compared to the Joint Typhoon Warning Center's best track ranged from 20 to 50 km, with weaker TCs showing larger errors. (Ho *et al.*, 2024) The AI models outperformed or matched the performance of the Automated Rotational Center Hurricane Eye Retrieval (ARCHER) product, which is typically reliant on data from both geostationary and polar-orbiting satellites. The absence of microwave data from polar-orbiting satellites led to larger errors in ARCHER, while the AI models achieved consistent and potentially operationally viable results using only geostationary satellite data.

(Xu *et al.*, 2023) A key objective in climate science research is to characterize extreme events in both current and future climate projections. Extreme climate events, such as hurricanes and heat waves, represent significant threats to infrastructure, property, and human safety. Satellites capture vast amounts of global data—approximately ten trillion terabytes annually—providing valuable insights into the dynamics of the climate system. Utilizing extreme climate analysis toolkits to assess features like cyclonic activity, pressure patterns, and other characteristics of tropical cyclones (TCs) is highly beneficial. With advancements in artificial intelligence (AI), particularly deep learning techniques, promising results have emerged in pattern recognition tasks, suggesting that these technologies can enhance our ability to predict and analyze tropical cyclones. Various deep-learning models will be employed to predict and evaluate hurricane events, as well as to assess the strength of tropical cyclones.

(Wei and Yang, 2021) Most current studies on tropical cyclone (TC) rapid intensification (RI) prediction rely on a subset of the SHIPS database and employ relatively simple model structures. However, the variables in the SHIPS database are derived from human expertise in TC intensity, often based on subjective thresholds, and their full potential has yet to be realized. (Jiang *et al.*, 2023) This study develops an advanced artificial intelligence (AI) system that simultaneously handles feature engineering, feature selection, data imbalance, prediction, and hyperparameter tuning, using the complete SHIPS dataset. The AI system aims to enhance the performance of existing RI prediction models and identify additional important SHIPS variables that were overlooked in previous research, based on variable importance scores. The results demonstrate a significant improvement, outperforming prior studies by approximately 21–50% in Probability of Detection (POD) while reducing the False Alarm Rate (FAR). This work establishes a baseline for future efforts in identifying new predictors using more sophisticated AI methods.

(Mercer and Grimes, 2017) Forecasting rapid intensification (RI) of Atlantic tropical cyclones (TCs) remains a significant challenge, with forecast skill scores only about 15% better than climatology. Traditionally, RI predictions have been made using linear discriminant analysis (LDA) with predictors optimized for RI, but no study has directly explored the use of machine learning (AI) for RI forecasting. (Rahman *et al.*, 2024) This study aims to evaluate RI predictability using proxy forecast model data and an ensemble of AI methods to generate probabilistic RI forecasts. Data from Atlantic RI events between 1985 and 2011 focused on valid times over water for each TC. These cases trained an AI ensemble optimized through three steps for RI prediction. (Gile *et al.*, 2021) First, backward elimination feature selection was applied to a mix of proxy forecast data, and LDA model predictors, and observed TC track information (including intensity and position) to refine the predictor set. Second, multiple configurations of three AI techniques—support vector machines (SVMs), artificial neural networks (ANNs), and random forests (RFs)—were tested using bootstrap-based cross-validation to identify the best settings for each method. Finally, the top-performing AI configurations were used to generate probabilistic RI forecasts, weighted by each ensemble member's cross-validation performance. The resulting probabilistic forecasts were comparable to those from the LDA model, but the ensemble's best skill surpassed the current LDA method by over 30% improvement compared to climatology.

(Matsuoka *et al.*, 2023) Forecasting rapid intensification (RI) of Atlantic tropical cyclones (TCs) remains a significant challenge, with current forecast skill only achieving approximately 15% improvement over climatological baselines. Historically, RI forecasts have relied on linear discriminant analysis (LDA) with predictors specifically tailored for this purpose, but the potential of machine learning (hereafter AI) for RI forecasting has not been directly explored. This study aims to evaluate the predictability of RI using proxy forecast model data and an ensemble of AI methodologies to produce probabilistic RI forecasts. Atlantic RI events from 1985 to 2011, occurring over water, were selected to train an AI ensemble optimized for RI prediction through a three-step process. First, backwards elimination was employed to refine the predictor set, integrating proxy forecast data, predictors from the existing LDA framework, and observed TC track information (e.g., intensity and position). Second, various configurations of three AI techniques—support vector machines (SVMs), artificial neural networks (ANNs), and random forests (RFs)—were rigorously evaluated using bootstrap-based cross-validation to identify optimal configurations for each method. Third, the most effective configurations were combined into an ensemble that produced probabilistic RI forecasts, with individual ensemble member contributions weighted according to their cross-validation performance. The resulting ensemble forecasts exhibited skill comparable to the current LDA approach, with the upper-performance threshold achieving over 30% improvement relative to climatology. This performance significantly surpasses the capabilities of the existing LDA framework, highlighting the potential of AI methods for advancing RI forecasting.

(Chen *et al.*, 2023) The onset of the South China Sea Summer Monsoon (SCSSM) is marked by a distinct seasonal shift in atmospheric circulation and convection patterns. Various indices have been proposed to determine the SCSSM onset date, but their results often vary significantly. This inconsistency complicates the identification of onset dates and hinders the evaluation of prediction skill. In 2021, for example, the onset date identified based on circulation criteria was 20 May, which was 12 days earlier than the date derived by incorporating convection criteria.

This study attributes the observed circulation-convection inconsistency primarily to the influence of tropical cyclone (TC) activity, modulated by the Madden-Julian Oscillation (MJO). The convection associated with TC "Yaas" (2021) served as a diabatic heat source at upper levels north of the South China Sea (SCS), driving the transition in circulation. Subsequently, TC "Cho-wan" (2021) in the western Pacific reinforced lower-level westerlies while suppressing moist convection over the SCS. Accurate predictions using the ECMWF S2S forecast system were achieved only after the formation of the MJO. Skillful MJO predictions during late spring could thus enable reliable forecasts of SCSSM establishment several weeks in advance.

5. Approaches Used in Predicting Hurricane

5.1. Machine Learning Techniques

Neural networks have emerged as a powerful tool for hurricane prediction, offering new capabilities in forecasting these complex atmospheric phenomena. These artificial intelligence systems can process vast amounts of meteorological data, including sea surface temperatures, wind patterns, atmospheric pressure, and historical storm tracks, to identify patterns and relationships that might not be apparent through traditional forecasting methods. By training on extensive historical hurricane data, neural networks can learn to recognize subtle atmospheric conditions that often precede hurricane formation and development. This makes them particularly valuable for predicting hurricane paths, intensity changes, and potential landfall locations. The ability of neural networks to handle non-linear relationships between various meteorological parameters has made them an increasingly important complement to conventional numerical weather prediction models, though they work best when used in conjunction with traditional forecasting methods and expert meteorological knowledge.

5.1.2. Support Vector Machines (SVMs)

Support Vector Machines (SVMs) represent a sophisticated machine-learning approach that has proven valuable in hurricane prediction. These algorithms excel at analyzing complex meteorological data by mapping it into higher-dimensional spaces where patterns become more distinguishable. In the context of hurricane forecasting, SVMs can effectively process multiple variables simultaneously - from sea surface temperatures and wind patterns to atmospheric pressure and humidity levels - to identify conditions conducive to hurricane formation and development. Their particular strength lies in their ability to create clear decision boundaries between different storm classifications and conditions, making them especially useful for predicting hurricane intensity categories. SVMs also demonstrate robust performance in handling noisy meteorological data and can maintain accuracy even with relatively smaller datasets than other machine learning methods. This makes them particularly valuable when working with historical hurricane records, where comprehensive data might not always be available for every storm event.

5.1.3. Random Forest

Random Forests are particularly well-suited for hurricane prediction due to their ability to handle complex, nonlinear relationships between multiple meteorological variables. The model works by creating an ensemble of decision trees, each trained on different subsets of the data, which collectively make predictions about hurricane formation and intensity.

For hurricane prediction, key input features typically include sea surface temperature, wind speed, atmospheric pressure, humidity, and precipitation patterns. These variables interact in complex ways - for example, warmer sea surface temperatures combined with low atmospheric pressure often create conditions favourable for hurricane development. Random Forests can automatically detect and learn from these interactions.

The prediction process begins with historical hurricane data, which is split into training and testing sets. Each decision tree in the forest examines different combinations of meteorological conditions that have historically led to hurricane formation. Some trees might focus more on wind patterns, while others might give more weight to temperature gradients. This diversity in the ensemble helps capture different aspects of hurricane development.

One significant advantage of using Random Forests for hurricane prediction is their ability to handle feature importance. The model can tell us which meteorological factors are most crucial in predicting hurricanes. For instance, it might reveal that sea surface temperature is the most important predictor, followed by wind shear patterns. This information is valuable for meteorologists in understanding hurricane dynamics.

Random Forests also provide probability estimates for their predictions, which is crucial for hurricane forecasting. Rather than simply predicting whether a hurricane will form, the model can estimate the likelihood of formation under given conditions, helping meteorologists make more informed decisions about issuing warnings. However, it's important to note that Random Forests have limitations in hurricane prediction. They work best with complete and accurate historical data, and their predictions are based entirely on past patterns. They may not perform as well with unprecedented weather conditions or climate change effects that deviate significantly from historical patterns. Therefore, they're typically used as one tool among many in hurricane forecasting, complementing other prediction methods and expert **m**eteorological analysis.

5.2. Deep Learning Approaches

5.2.1. Convolutional Neural Networks (CNNs)

CNNs are a cornerstone of hurricane detection, primarily used to analyze satellite imagery and radar data. These networks excel in identifying spatial features such as the eye of the hurricane, spiral rainbands, and cloud structures. By learning intricate patterns from images, CNNs can classify hurricane intensity and provide insights into storm development. Pre-trained models like ResNet and VGG are often fine-tuned with meteorological datasets for this purpose, or custom architectures are designed specifically for atmospheric data.

5.2.2. Recurrent Neural Networks (RNNs) and LSTM Models

RNNs and LSTMs are well-suited for handling sequential data, making them ideal for analyzing time-series information such as wind speed, pressure variations, and temperature changes. These models are frequently employed to predict hurricane trajectories and formation by learning temporal dependencies in the data. For instance, they can anticipate a tropical depression's evolution into a hurricane or forecast its movement based on historical trends.

5.2.3. Autoencoders

Autoencoders are unsupervised models valuable for feature extraction and anomaly detection in weather data. They help identify unusual atmospheric patterns that may indicate hurricane formation and can also enhance the quality of satellite images by reducing noise. This capability improves the clarity of data, allowing for more accurate analysis.

5.2.4. Generative Adversarial Networks (GANs)

GANs play a crucial role in creating synthetic data and improving image quality. They generate realistic hurricane scenarios for training purposes, addressing the challenge of limited labeled data. Additionally, GANs enhance the resolution of satellite images, enabling better recognition of fine details such as storm cloud patterns and structural changes.

5.2.5. Transfer Learning

Transfer learning involves adapting pre-trained deep learning models to hurricane detection tasks. By fine-tuning models that were originally trained on general image datasets, researchers can significantly reduce training time and computational demands. This approach is particularly effective for rapid deployment of hurricane monitoring systems.

5.2.6. Hybrid Models

Hybrid models combine the strengths of different deep-learning approaches to achieve superior performance. For example, CNNs can extract spatial features from satellite imagery, while LSTMs handle temporal data, allowing the integrated model to predict hurricane paths and intensities more accurately. Physics-informed neural networks, which embed meteorological laws into deep learning frameworks, are also gaining traction for precise and reliable predictions.

6. Prisma Diagram (Flow Chart)

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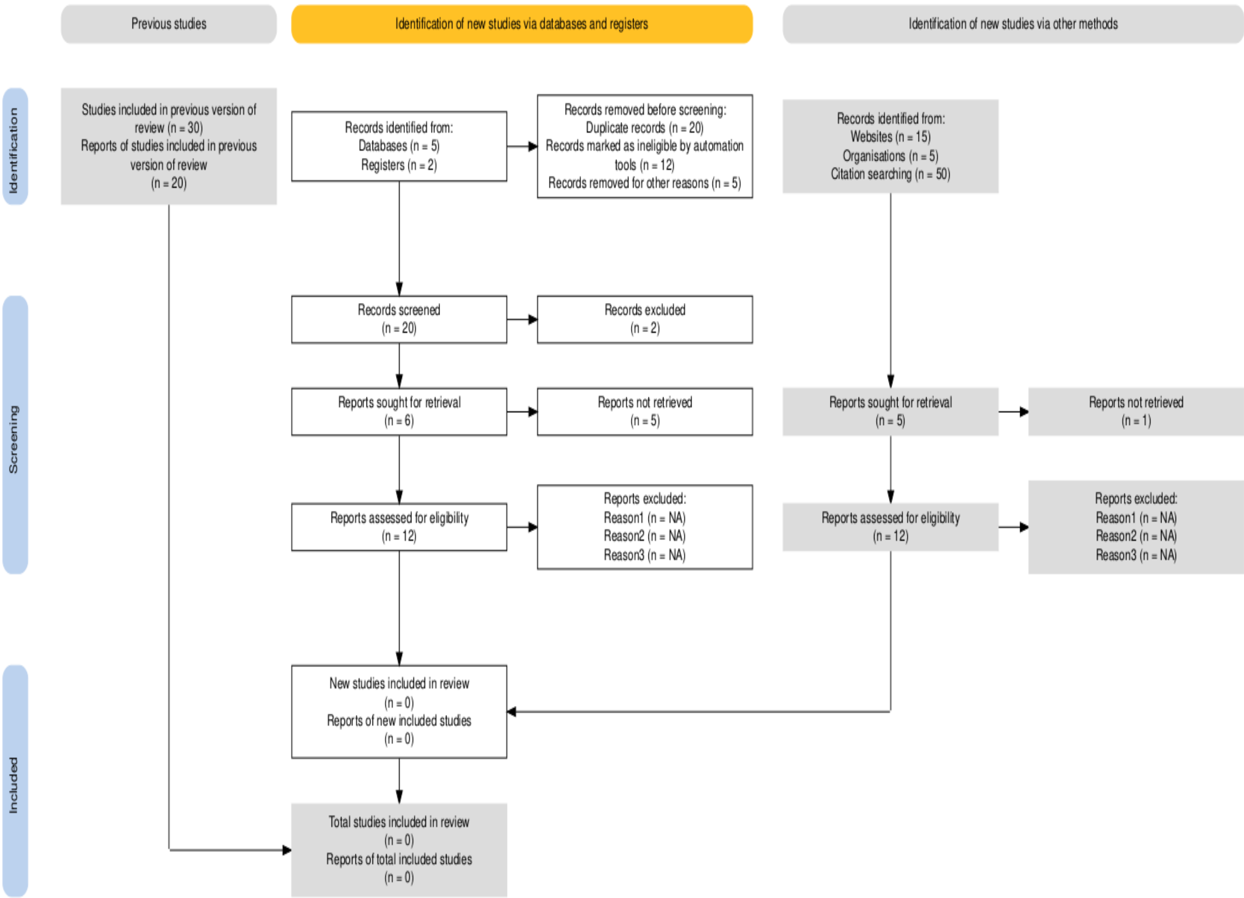

Figure 1. Prisma Diagram on the Systematic Review on Prediction of Hurricanes using AI Techniques

7. Results and Discussion

7.1. Explanation of Research Questions

RQ1: How do different machine learning algorithms compare in their effectiveness for predicting hurricane trajectories?

Machine learning algorithms exhibit varying effectiveness in predicting hurricane trajectories based on their ability to handle complex, non-linear relationships and the nature of the data. Artificial Neural Networks (ANNs) excel at modeling intricate interactions but require large datasets and are computationally intensive. Support Vector Machines (SVMs) perform well with smaller datasets and can classify trajectory clusters effectively but struggle with scalability and highly non-linear dynamics. Random Forests (RFs) are robust to noise and overfitting, offering reliable predictions and feature interpretability, although they may not capture complex interactions as effectively as ANNs. Gradient Boosting Machines (e.g., XGBoost, LightGBM) strike a balance, performing well with structured data and smaller datasets but demand careful hyperparameter tuning. Deep learning architectures, including Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and Convolutional Neural Networks (CNNs), are particularly suited for sequential data like time series or spatial data from satellite imagery, making them powerful for trajectory prediction, though they require extensive data and computational resources. Ultimately, the choice of algorithm depends on the dataset characteristics, computational resources, and the specific problem requirements.

RQ2: What are the most accurate machine-learning techniques for forecasting hurricane intensity?

The most accurate machine learning techniques for forecasting hurricane intensity often depend on their ability to handle non-linear relationships, incorporate diverse data sources, and provide probabilistic predictions. Deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs), are highly effective for intensity prediction due to their capacity to process spatial data (e.g., satellite imagery) and temporal sequences (e.g., atmospheric conditions over time). LSTMs, in particular, are adept at capturing temporal dependencies critical for intensity changes. Gradient Boosting Machines (e.g., XGBoost, LightGBM) are also widely used, as they excel with structured meteorological data, such as wind speed, sea surface temperature, and pressure fields, offering robust performance even with relatively small datasets. Random Forests (RFs) are valued for their reliability and ability to provide feature importance, aiding interpretability in operational forecasting. Hybrid approaches that combine physical models with machine learning, such as using machine learning to refine outputs from numerical weather prediction models, have also shown promise. Ultimately, the most accurate technique often involves an ensemble approach that leverages the strengths of multiple methods, optimizing predictions by combining their outputs.

RQ3: What are the current limitations and challenges in applying machine learning to hurricane forecasting?

Applying machine learning (ML) to hurricane forecasting presents several limitations and challenges, ranging from data availability to model interpretability. A significant limitation is the **quality and quantity of data**, as hurricanes are rare events, and historical datasets may be insufficient to train complex models effectively. Additionally, these datasets often lack uniformity, with missing or inconsistent measurements across variables like wind speed, sea surface temperature, and atmospheric pressure. **Spatial and temporal resolution** is another challenge, as ML models require high-resolution data to accurately capture the fine-scale processes that influence hurricane behaviour, but such data can be computationally expensive to process. Another critical issue is **generalization**, where models trained on past hurricanes may struggle to predict new ones under changing climate conditions or in regions with limited historical data. Interpretability of ML models is also a concern, as many algorithms, particularly deep learning, operate as "black boxes," making it difficult to understand the reasoning behind predictions—a limitation in operational forecasting where trust and transparency are vital. Moreover, integration with physical models poses challenges, as ML methods must complement rather than conflict with established numerical weather prediction models, which are grounded in physical laws. Finally, real-time forecasting requires models that are computationally efficient and capable of providing predictions under tight time constraints, which is a barrier for resource-intensive algorithms like deep neural networks. Addressing these challenges is critical to fully realizing the potential of ML in improving hurricane forecasting accuracy and reliability.

8. Conclusion

The systematic review on hurricane prediction utilizing machine learning techniques reveals significant advancements in forecasting capabilities. Machine learning algorithms, including neural networks, random forests, and support vector machines, demonstrate remarkable potential in enhancing hurricane trajectory and intensity predictions. By integrating diverse data sources such as satellite imagery, historical hurricane records, and climate models, researchers have developed more sophisticated predictive frameworks that can potentially improve early warning systems and disaster preparedness. Despite challenges posed by the complex atmospheric dynamics and inherent variability of hurricane behaviour, these ML techniques offer promising insights into more accurate and timely hurricane forecasting. The research underscores the critical importance of interdisciplinary collaboration between meteorologists and data scientists, emphasizing the need for continuous model refinement, advanced computational infrastructures, and innovative approaches to capture the intricate patterns of hurricane formation and movement. Ultimately, the systematic review highlights machine learning's transformative potential in mitigating hurricane-related risks and advancing our understanding of these powerful natural phenomena.

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