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Exploring Technological Innovation in Wave Forecasting Using Machine Learning: A Literature Analysis

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ABSTRACK

In the face of rapid technological advancements, innovations in wave forecasting are increasingly essential for effectively addressing the complex impacts of climate change. This study aims to explore technological developments in wave forecasting that can manage the complexities related to climate change and enhance the accuracy and efficiency of predictions in dynamic marine environments. Employing a qualitative approach through a Systematic Literature Review (SLR) methodology, the research focuses on literature from databases such as Scopus, DOAJ, and Google Scholar, specifically targeting publications from 2014 to 2024. Recent findings reveal that advancements in machine learning technologies, including deep learning, ensemble learning, transfer learning, and data augmentation, have significantly improved the precision and efficiency of wave forecasting models. Techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been particularly effective in capturing complex, non-linear patterns within wave data, enhancing the overall prediction accuracy. Ensemble learning methods have further contributed by increasing the stability and robustness of forecasts. Moreover, transfer learning and data augmentation play vital roles in adapting these models to rapidly changing environmental conditions, making them highly relevant in the context of climate change. These approaches are crucial for models to remain adaptable and responsive to dynamic oceanic conditions influenced by climate variability. The insights derived from this study are expected to provide valuable direction for the future development of machine learning-based wave forecasting models, emphasizing the need for innovative techniques that can accommodate the complexities and uncertainties brought about by climate change.

Keyword: Technological Innovation, Wave Forecasting, Machine Learning, Prediction Models

INTRODUCTION

Wave forecasting plays a crucial role in various sectors, including maritime navigation, coastal safety, renewable energy, and disaster mitigation. In maritime navigation, accurate wave condition information is essential for determining safe and efficient sailing routes, thereby reducing the risk of accidents and optimizing travel time and costs (Aslam et al., 2020). In the coastal safety sector, precise wave forecasting aids in flood and coastal erosion management, as well as in preparing evacuation and protection measures for coastal communities (Arkema et al., 2017). Additionally, in the development of renewable energy, particularly wave energy, a deep understanding of wave patterns enables the optimization of device design and placement, thereby enhancing energy production efficiency (Garcia-Teruel & Forehand, 2021). In disaster mitigation efforts, such as tsunamis and storms, accurate wave prediction is critical for providing early warnings and reducing the destructive impact of these events (Angove et al., 2019).

In the past decade, technology has undergone significant advancements to support wave forecasting, particularly through progress in sensors, satellites, and numerical models. Advanced sensors can now measure various ocean parameters in real-time, such as wave height, currents, sea surface temperature, and salinity, all of which are crucial data for developing predictive wave models (Isern-Fontanet et al., 2017). Additionally, satellite technology has advanced with higher resolution and observation frequency, enabling more detailed and extensive monitoring of ocean conditions (Vinogradova et al., 2019). Modern satellites can provide accurate and comprehensive data on atmospheric and oceanic conditions, which are then used to inform forecasting models.

Furthermore, numerical models have been refined with greater computational capabilities and more complex algorithms, allowing for more accurate simulations of wave dynamics (Sonnewald et al., 2021). The combination of data from sensors and satellites, processed through advanced numerical models, has significantly enhanced our ability to predict ocean waves more accurately and swiftly (Shutler et al., 2016).

Machine learning is an innovative technology that has revolutionized various fields, ranging from healthcare and finance to environmental science. Essentially, machine learning is a branch of artificial intelligence (AI) that enables computer systems to learn from data and make predictions or decisions without being explicitly programmed (Jordan & Mitchell, 2015). This technology operates by identifying patterns or trends within large and complex datasets, which may be challenging for humans or traditional analytical methods to discern.

Machine learning offers a novel approach to data processing through the use of algorithms that can automatically improve their performance as more data is analyzed (Ling, 2023). With this capability, machine learning can produce more accurate and adaptive predictions in response to changing conditions or continuously evolving data. In the context of wave forecasting, for example, machine learning can process vast amounts of historical and real-time data, such as weather conditions, ocean currents, and wave heights, to predict wave patterns more effectively (James et al., 2018).

Machine learning has been widely applied in wave forecasting, offering a new and more accurate and adaptive approach. Algorithms such as neural networks and support vector machines have been used to process complex ocean data, including wave heights, ocean currents, and weather conditions. Research indicates that machine learning techniques like the Ensemble of Extreme Learning Machine (Ens-ELM) outperform Extreme Learning Machine (ELM), Online Sequential ELM (OS-ELM), and Support Vector Regression (SVR) in predicting daily wave heights (Kumar et al., 2018). Other techniques, such as multilayer perceptron, gradient boosting decision trees, and ensemble methods, also enhance the accuracy of the Puertos del Estado (PdE) forecasting system, reducing the prediction error of numerical models by approximately 36% (Gracia et al., 2021).

Sequential learning algorithms like Minimal Resource Allocation Network (MRAN) and Growing and Pruning Radial Basis Function (GAP-RBF) are more effective than SVR and ELM, with MRAN demonstrating a more efficient architecture (kumar et al., 2017). The use of machine learning in ocean data analysis is increasingly popular due to its ability to handle large volumes and dimensions of data, with significant applications in marine environmental protection and responses to extreme weather (Lou et al., 2023). In Monterey Bay, a machine learning framework successfully replicated wave heights with an error of 9 cm and correctly identified over 90% of characteristic periods, while reducing computation time compared to physics-based models (James et al., 2018). Climate change affecting wave patterns drives the need for more advanced and adaptive technologies, such as machine learning and complex numerical models, to address these challenges and dynamically update prediction models.

Global challenges such as climate change have a significant impact on sea wave patterns, which in turn create an urgent need for continuous technological innovation to maintain forecasting accuracy. Hünicke et al. (2015) observed changes in sea level and wind waves in the Baltic Sea over the past 200 years, finding that the relative sea level in the Bothnian Bay decreased by 8.2 mm per year, while in the southern Baltic Sea, there was a slight rise, with an increasing trend in sea level primarily during the winter season. (Woodworth et al., 2019) discussed the greater and more complex variability of coastal sea levels compared to deep oceans; however, aspects such as the influence of waves and river flows on sea level records remain under-researched.

(Reguero et al., 2019) found that the global sea wave power has increased by 0.4% per year since 1948 due to sea surface warming, making it an important indicator of climate change. Meanwhile, (Melet et al., 2020) estimated a 20-year average change in "wave setup" on sandy coastlines due to climate change based on the RCP 8.5 scenario, with results indicating small but significant regional variations that need to be incorporated into regional sea level change projections, particularly for studies of extreme events.

Several key studies have been conducted on the integration of machine learning and technological innovation in wave forecasting, contributing significantly to the enhancement of prediction models' accuracy and efficiency. For instance, a study utilizing deep learning to predict wave height with high accuracy through the analysis of historical weather and wave data demonstrated that this algorithm is capable of capturing complex and nonlinear patterns (Afzal et al., 2023). Another study employed support vector machines to predict sea wave changes based on various environmental parameters, finding that this method can improve prediction reliability compared to traditional statistical models (Imani et al., 2018).

Additionally, research leveraging ensemble learning showed that combining various machine learning algorithms can yield more stable and accurate predictions under fluctuating sea conditions (Zhang et al., 2022). Although these studies have laid a strong foundation for the application of machine learning in wave forecasting, there remains room for further exploration, particularly in handling highly variable and dynamic data and developing models that are more adaptive to climate change.

Research findings have demonstrated the successful application of machine learning in wave forecasting; however, there remains a gap in the adaptation of models to climate change, which dynamically affects wave patterns. Previous studies have predominantly focused on short-term prediction accuracy and have not fully integrated long-term challenges, such as regional variability and extreme phenomena in sea level projections. Therefore, this study aims to explore technological innovations in wave forecasting that can address the complexities of climate change while enhancing the accuracy and efficiency of predictions in ever-changing sea conditions.

METHODOLOGY

This study employs a Systematic Literature Review approach to explore technological innovations in wave forecasting that can address the complexities of climate change while enhancing prediction accuracy and efficiency. The process begins with formulating the research problem, which focuses on identifying the latest technologies and the application of machine learning in wave forecasting. Inclusion criteria encompass peer-reviewed journal articles, international conference papers, books, and relevant research reports published between 2014 and 2024, in English, discussing the application of machine learning and recent technological innovations. Exclusion criteria include opinion articles, editorials, letters to the editor, non-peer-reviewed publications, those published before 2014, and studies not related to machine learning or technological innovations in wave forecasting.

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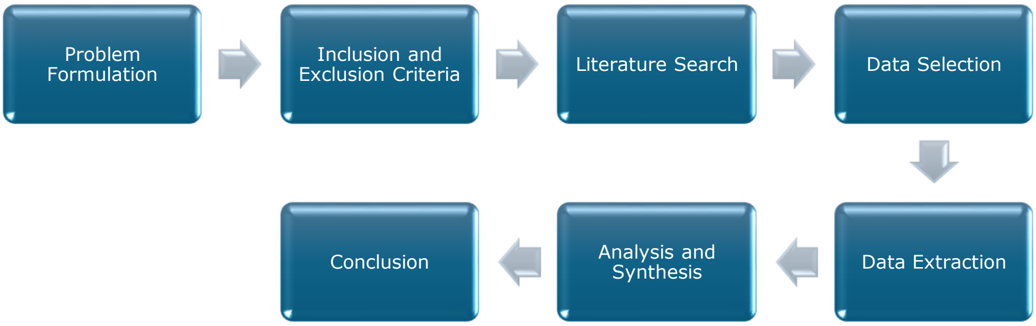
Figure 1. Flow of Research Implementation



Source: Author, 2024

The research methodology involves searching for literature through databases such as Scopus, DOAJ, and Google Scholar using keywords like Technological Innovation, Wave Forecasting, Machine Learning, and Prediction Models. Relevant data will be selected based on the predefined criteria and then extracted to obtain information about methodologies, results, and technological innovations. The extracted data will be analyzed to identify patterns and trends and to assess the effectiveness of machine learning in wave forecasting. The analysis will be synthesized to provide a comprehensive overview of advancements and challenges in the field, culminating in conclusions that offer recommendations for further research and development.

RESULTS AND DISCUSSION

After conducting an in-depth literature review, we identified several relevant studies that provide significant insights supporting the focus and objectives of this research. These studies offer critical contributions that enrich our understanding of the topic, particularly in the context of technological innovation and the adaptation of wave forecasting to the challenges posed by climate change. The information gathered from these studies not only enhances the depth of our analysis but also provides a robust foundation for developing a more comprehensive conceptual framework for this research. The additional knowledge derived from these studies is invaluable in addressing the research questions posed and in supporting the development of more accurate and efficient wave forecasting models based on machine learning. The findings from these studies have been organized and synthesized in Table 1.

Table 1. Research Variables Discussed in the article

No	Focus or Scope	Authors	Insights or Research Variables Discussed
1	Deep Learning in Wave Forecasting	Chen et al. (2020), A. Ali et al. (2021), Jörges et al. (2023), M. Ali et al. (2021)	Use of Deep Learning such as CNN and RNN to capture complex and non-linear patterns in wave data. Improved prediction accuracy through these technologies over traditional methods.
2	Ensemble Learning in Wave Forecasting	Mienye & Sun (2022), Freeman et al. (2015), Mittendorf et al. (2022), Troin et al. (2021)	Implementation of Ensemble Learning such as Random Forests and Gradient Boosting Machines to combine the power of various models to produce more stable and accurate

No	Focus or Scope	Authors	Insights or Research Variables Discussed
			predictions. This method is also used to deal with diverse climate scenarios.
3	Adaptive and Online Learning	Moubayed et al. (2018), Zhang et al. (2023)	Development of Online/Adaptive Learning to handle changing data patterns, as well as improved model performance under dynamic ocean conditions.
4	Transfer Learning in Climate Adaptation	Guan (2020), Bellagarda et al. (2022), Lu et al. (2015)	Use of Transfer Learning to accelerate model adaptation to rapid climate change, by utilizing existing data for new conditions. This innovation helps the model adapt to fast-changing environmental dynamics.
5	Data Augmentation for Climate Challenges	Ahmad et al. (2018), Hipsey et al. (2015)	Application of Data Augmentation to expand the variability of training data, including extreme conditions and regional variability, to improve model robustness and accuracy in the face of climate change challenges.
6	Impact of Climate Change on Wave Forecasting	Shi et al. (2020), Moazami et al. (2019)	This research discusses how machine learning models, especially in the context of climate change, can be more effective in dealing with regional variability and extreme phenomena than traditional methods. The use of historical data covering long-term climate variability is the main focus.

Source: Author, 2024

Table 1 categorizes recent studies focused on the application of machine learning technologies in wave forecasting, particularly in the context of climate change adaptation. These studies include the use of deep learning techniques, such as CNNs and RNNs, to enhance prediction accuracy by capturing complex non-linear patterns. Additionally, ensemble learning methods are highlighted for their ability to produce more stable predictions through the combination of various models. Innovations in adaptive and online learning are also noted, addressing the challenge of continuously evolving data patterns. Moreover, transfer learning techniques are employed to expedite model adaptation to new climate conditions. Data augmentation is utilized to improve model robustness in extreme conditions. Other studies emphasize the impact of climate change on wave forecasting, with a focus on regional variability and extreme phenomena that are difficult to predict using traditional methods. These topics will be explored in greater detail in the following discussion.

1. The latest technological innovations applied in ocean wave forecasting using machine learning

Recent advancements in wave forecasting models using machine learning incorporate various sophisticated methods that have demonstrated improved accuracy and efficiency in

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predictions (Chen et al., 2020). A major innovation is the application of deep learning, which utilizes deep neural networks to capture complex and non-linear patterns in wave data. Techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have shown superior capabilities in predicting wave heights and patterns more accurately compared to traditional methods (Guan, 2020). Additionally, ensemble learning techniques play a crucial role by combining the outputs of multiple machine learning algorithms to produce more stable and reliable predictions (Mienye & Sun, 2022). This approach, which includes methods such as Random Forests and Gradient Boosting Machines, integrates the strengths of various models to reduce prediction errors and enhance overall performance (Freeman et al., 2015).

The application of advanced machine learning technologies, such as deep learning and ensemble learning, significantly impacts the accuracy and efficiency of wave forecasting models compared to traditional methods (A. Ali et al., 2021). Deep learning technologies, with their ability to capture complex and non-linear patterns in data, have been shown to enhance prediction accuracy by reducing estimation errors common in classical statistical models (Ahmad et al., 2018). Models like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) offer improved capabilities for processing temporal and spatial data, resulting in more precise predictions (Jörges et al., 2023). Meanwhile, ensemble learning combines the strengths of various machine learning algorithms, such as Random Forests and Gradient Boosting Machines, to produce more stable and consistent predictions (Mittendorf et al., 2022). These technologies also demonstrate higher effectiveness in addressing the complexities of climate change by adapting to evolving data dynamics. In the context of climate change, machine learning models can better account for regional variability and extreme phenomena compared to traditional methods, which may be less responsive to rapid and drastic climate fluctuations (Shi et al., 2020).

These trends highlight significant advancements in the application of machine learning for wave forecasting. The use of deep learning models, such as CNNs and RNNs, has proven superior in capturing the complexity of wave data compared to traditional methods, particularly in identifying non-linear and hard-to-predict patterns. Ensemble learning enhances prediction stability and accuracy by combining multiple models, while transfer learning accelerates model adaptation to new conditions by leveraging knowledge from existing datasets. Data augmentation introduces additional variability in training data, crucial for ensuring that models adapt well to extreme conditions and regional variations commonly encountered in wave forecasting. However, several challenges accompany these advancements.

Deep learning, despite its effectiveness, demands substantial computational resources and long training times, which may pose practical limitations, especially in resource-constrained environments. While ensemble learning improves stability, it also increases overall model complexity, potentially leading to difficulties in result interpretation and risks of overfitting if not carefully managed. Transfer learning's success heavily relies on the relevance and quality of prior datasets, meaning that suboptimal datasets could hinder performance. Additionally, the effectiveness of data augmentation depends on how well these techniques replicate real-world conditions, which is vital for practical applications.

2. Key challenges in using machine learning for ocean wave forecasting in the context of climate change

The primary challenges related to data variability and dynamic sea conditions impacting machine learning model performance include the instability of data arising from rapid environmental fluctuations and changes in wave patterns that are difficult to predict (Zheng et al., 2020). This variability can lead to inaccuracies in predictions and reduce model

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accuracy. Researchers address these challenges through several innovative approaches. One method involves the continuous updating and training of machine learning models to handle evolving data over time (Moubayed et al., 2018), including the integration of data augmentation techniques that expand training data variability to cover extreme conditions and regional variability. Additionally, the application of algorithms capable of adaptively adjusting to changing data patterns, such as online learning or adaptive learning models, has been introduced to enhance model performance in dynamic sea conditions (Zhang et al., 2023). These approaches enable models to continuously learn and refine predictions based on the most recent data, thereby improving resilience and accuracy in wave forecasting amidst evolving climate uncertainties.

Existing machine learning models adapt to the continuously evolving climate by employing several strategies to address the associated complexities and dynamics. One major approach is integrating historical data that encompasses long-term climate variability and extreme phenomena, allowing models to recognize changing patterns and adapt to new conditions (Moazami et al., 2019). These models often utilize feature engineering techniques to incorporate additional relevant variables, such as sea surface temperature and wind patterns, which can influence wave patterns.

Furthermore, the use of ensemble learning methods enables the combination of multiple predictive models to handle various climate scenarios simultaneously, thereby enhancing model resilience to data uncertainties (Troin et al., 2021). Transfer learning models are also applied to transfer knowledge from existing data to new conditions, accelerating adaptation to rapid climate changes (Bellagarda et al., 2022). Despite these advancements, challenges remain in accounting for extreme phenomena and long-term changes due to the high complexity and variability involved.

The research findings indicate that the primary challenges in applying machine learning for wave forecasting are closely tied to the uncertainty posed by data variability and rapid environmental changes due to climate change. This variability challenges model stability and requires continuous updates and responsive adaptations to the latest data. By integrating historical data and employing adaptive learning algorithms, models can improve prediction accuracy and resilience. Ensemble learning provides advantages in handling diverse and complex climate scenarios, while transfer learning enables quicker adaptation to changing conditions. However, these approaches also present limitations.

Continuous model updates and training are crucial but demand significant computational resources and up-to-date data, which may not always be available. Data augmentation and feature engineering extend training data coverage, yet their effectiveness hinges on the appropriate selection of features and the relevance of augmented data to actual conditions. While ensemble and transfer learning offer robust solutions to data uncertainty, they also increase model complexity, potentially leading to challenges like overfitting and higher computational requirements.

3. Trends and future directions in the development of machine learning technology for ocean wave forecasting

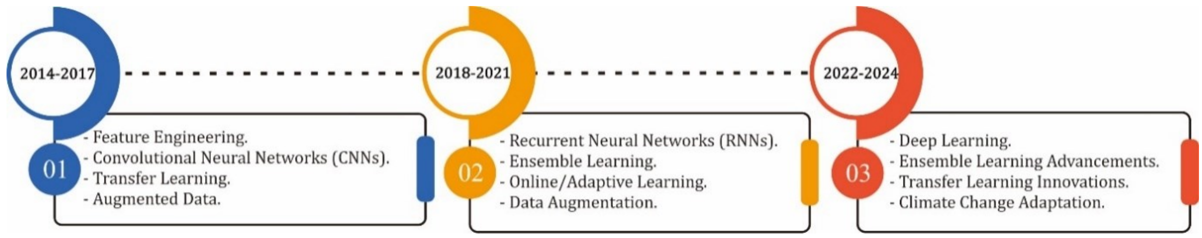
Recent trends in machine learning technology integrated with wave forecasting encompass several new methods and innovative approaches emerging from current research. A major trend is the application of deep learning, particularly models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have demonstrated superior capabilities in capturing complex and non-linear patterns in wave data (M. Ali et al., 2021). Additionally, ensemble learning methods have gained popularity due to their ability to combine results from multiple machine learning models, such as Random Forests and Gradient Boosting Machines, to produce more stable and accurate predictions (Mienye & Sun, 2022).

Another emerging approach is the use of transfer learning techniques, which leverage knowledge from existing datasets to enhance model performance in new conditions (Lu et al., 2015). Finally, the integration of augmented data, which expands training data variability to include extreme conditions and regional variability, is also a key focus, aiding models in adapting to changing environmental dynamics (Hipsey et al., 2015). All these innovations contribute to improved accuracy and efficiency in wave forecasting amidst the ongoing challenges posed by climate change.

These trends highlight significant advancements in machine learning for wave forecasting. Deep learning models like CNNs and RNNs excel in capturing the complex, non-linear patterns of wave data, outperforming traditional methods. Ensemble learning enhances prediction stability and accuracy by combining multiple models, while transfer learning accelerates model adaptation to new conditions by leveraging prior datasets. Data augmentation introduces variability in training data, crucial for adapting to extreme conditions and regional differences.

Despite these advancements, challenges remain. Deep learning requires substantial computational resources and long training times, which can be limiting in resource-constrained environments. Ensemble learning, while improving accuracy, increases model complexity, potentially leading to difficulties in result interpretation and risks of overfitting. Transfer learning's effectiveness depends on the quality and relevance of prior datasets, and data augmentation's success relies on accurately replicating real-world conditions for practical applications.

Figure 2. Research Variables Contained in this Study



Source: Author, 2024

Figure 2 illustrates the significant advancements in wave forecasting technology over recent years, highlighting the increasing sophistication in the use of key research variables. During the 2014-2017 period, the primary focus was on "Feature Engineering" to incorporate variables such as sea surface temperature and wind patterns into forecasting models. Additionally, there was an initial implementation of "Convolutional Neural Networks (CNNs)" aimed at capturing non-linear patterns within wave data. "Transfer Learning" also began to be applied, leveraging existing data to enhance performance in new conditions, while the integration of "Augmented Data" was introduced to increase the variability of training data, including under extreme conditions. In the 2018-2021 period, there was a marked increase in the use of "Recurrent Neural Networks (RNNs)" for temporal data prediction, alongside the growing popularity of "Ensemble Learning" techniques, such as Random Forests and Gradient Boosting Machines, which contributed to more stable predictions.

This era also saw the introduction of "Online/Adaptive Learning" models designed to adapt to continuously changing data patterns, supported by broader application of "Data Augmentation" techniques to address the challenges posed by climate change. Moving into the 2022-2024 period, advancements in "Deep Learning" technologies, particularly CNNs and RNNs, further enhanced predictive accuracy. Simultaneously, "Ensemble Learning" techniques were further refined to combine various models for better handling of diverse climate scenarios. Innovations in "Transfer Learning" continued to evolve, speeding up model adaptation to rapid climate changes, with a significant emphasis on "Climate Change Adaptation" strategies to address increasingly complex environmental dynamics, including the management of extreme events and long-term variability.

CONCLUSION

Recent evaluations of research indicate that innovations in machine learning technologies, particularly through deep learning, ensemble learning, transfer learning, and data augmentation, have significantly enhanced the accuracy and efficiency of wave forecasting. Models such as CNNs and RNNs have proven effective in capturing the complexity of non-linear data, while ensemble learning has contributed to increased prediction stability. Additionally, transfer learning and data augmentation play crucial roles in accelerating model adaptation to rapidly changing environmental conditions, particularly in addressing the challenges posed by climate change. However, there remain significant obstacles, including the high computational demands, reliance on high-quality data, and the risk of overfitting due to the increasing complexity of these models.

These gaps highlight urgent research opportunities for the future, including the development of more computationally efficient machine learning algorithms that can perform well even with limited resources. Further research is needed to enhance the effectiveness of data augmentation in replicating real-world conditions and to develop more adaptive transfer learning methods capable of responding to unexpected environmental changes. Moreover, the integration of broader oceanographic data and the development of predictive models capable of handling extreme conditions are essential to ensure that wave forecasting remains reliable and sustainable in the long term.

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