International Journal of Advanced Trends in Multidisciplinary Research
ISSN: 3139-0986, Volume 2 Issue 7
July 2026, PP 1-7

Advanced Machine Learning Framework for Ocean Wave Energy Prediction

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Abstract **– Ocean wave energy has great potential for supporting sustainable power production, is continuously available, and has a high energy density, making it one of the most promising renewable energy resources. It is crucial to accurately predict ocean wave properties such as significant wave height (SWH), wave period, and wave energy flow in order to efficiently use wave energy. Prediction accuracy under changing sea conditions is limited by traditional numerical forecasting models' inability to incorporate the ocean's extremely nonlinear, dynamic, and unpredictable character. Through an examination of current developments in ML, DL, ensemble learning, and hybrid prediction models, this research lays forth a framework for intelligent wave energy forecasting that is based on machine learning. The suggested framework takes a look at some of the most popular algorithms for making predictions about the future, such as ANNs, LSTM, CNNs, RF, XGBoost, Transformer-based models, and hybrid ML techniques. These algorithms can predict things like wave height, wave period, and energy generation potential. Hybrid deep learning architectures that include both spatial and temporal feature extraction are more resilient to the unpredictable ocean conditions and provide more accurate forecasts, according to a comparative study. Common metrics used in forecasting for performance assessment include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^3). In addition, the suggested forecasting framework is fully integrated into a web application built on Django. This web app lets users analyse oceanographic data, run prediction models using machine learning, see the outcomes of the forecasts visually, and keep an eye on the wave energy production via an interactive dashboard. The suggested system is an intelligent decision-support platform that can optimise wave energy converters, manage renewable energy sources, and integrate ocean wave energy into current power systems efficiently.**

Keywords **– Wave Energy Forecasting, Machine Learning, Deep Learning, Ocean Wave Prediction, Significant Wave Height, Renewable Energy, Random Forest, XGBoost, LSTM, CNN, Django Web Application.**

I. INTRODUCTION

Researchers are working to develop renewable energy supplies that may lessen our reliance on fossil fuels and lessen the environmental effect in response to the growing demand for sustainable energy on a worldwide scale. Due to its high energy density, constant availability, and predictable nature, ocean wave energy has become one of the most attractive renewable energy solutions among many others. Wave energy is a promising alternative for future renewable energy systems since its power generating capacity is essentially constant, unlike solar and wind energy, which are affected by weather fluctuation and daylight conditions. However, precise forecasting of ocean wave properties under varied maritime circumstances is necessary for efficient use of this resource. [1, 2]

Offshore renewable energy infrastructures including Wave Energy Converters (WECs) rely heavily on wave energy forecasts for their design, operation, and optimisation. Improved power generating efficiency, enhanced equipment safety, reduced maintenance costs, and optimised grid integration are all possible outcomes of accurate parameter prediction for waves, including Significant Wave Height (SWH), period, direction, and energy flow. Sea transportation, coastal engineering, offshore building, and catastrophe management all benefit from accurate forecasts since they provide up-to-the-minute information about ocean conditions. [3, 4]

Statistical prediction methods and numerical oceanographic models provide the backbone of conventional wave forecasting approaches. Marine forecasting has benefited greatly from these methods, although they are resource intensive and may not be able to capture the ocean waves' complex dynamics and nonlinear behaviour. Especially when it comes to situations involving long-term predictions, typical forecasting models aren't very good due to environmental uncertainties, seasonal changes, and complicated interactions between atmospheric and oceanic factors. [5, 6]

A new generation of data-driven methods for simulating intricate marine ecosystems has emerged because to developments in ML and DL. Without depending just on predetermined mathematical equations, these methods may autonomously discover hidden correlations from historical oceanographic facts. Sea data contains nonlinear temporal and spatial dependencies, which algorithms like ANNs, SVMs, Random Forests, XGBoost, LSTM networks, CNNs, and Transformer-based architectures have successfully captured. These algorithms have shown outstanding performance in forecasting wave height, period, and energy generation. “7” through “11”
Hybrid forecasting models, which combine several ML and DL approaches to strengthen the model and increase prediction accuracy, have recently attracted a lot of attention from academics. These hybrid methods reduce prediction errors while efficiently capturing the spatial and temporal features of ocean wave dynamics via the combination of complementing learning capacities. Combining several prediction models to increase dependability of forecasts and generalisation performance under changing environmental circumstances is what

ensemble learning does, and it has demonstrated encouraging results. pages 12–15

There are still a number of obstacles in intelligent wave energy forecasting, even with these major improvements. The building of models is typically made more difficult by the presence of missing values, measurement noise, seasonal changes, and very dynamic environmental patterns in oceanographic datasets. Additionally, there are still open research questions including the best learning algorithms to use, the best way to optimise hyperparameters, and how to guarantee that models generalise across diverse areas. Finding accurate forecasting models that are well-suited to real-world renewable energy applications requires a thorough comparison of current machine learning approaches. from [16] forward to [19]

Through an examination of current advancements in artificial intelligence approaches used by renewable ocean energy systems, this study offers a thorough evaluation and analysis of Machine Learning-based Wave Energy Forecasting. The forecasting accuracy, computational efficiency, resilience, and practical application of several forecasting systems are compared. These approaches include deep learning architectures, ensemble learning methodologies, hybrid prediction frameworks, and standard machine learning algorithms. Furthermore, a web application built using the Django framework is added to the proposed forecasting framework. This web application allows users to examine oceanographic data, run forecasting models, and see the outcomes of these analyses via an interactive online interface.

II . RELATED RESEARCH

The rising need for smart energy management systems and dependable renewable energy sources has made ocean wave energy forecasting a hotspot for study. Efficiency improvements in Wave Energy Converters (WECs), optimisation of offshore power production, assistance for marine transportation, and enhancement of coastal engineering applications all depend on accurate wave characteristic predictions. In an effort to enhance prediction accuracy in the face of ever-changing ocean circumstances, researchers have put forth a plethora of forecasting methods based on numerical simulations, deep learning architectures, machine learning algorithms, and statistical models within the last decade.

Studies on wave forecasting in the early days mostly used numerical wave models and conventional statistical methods that drew on meteorological and oceanic data from the past. When faced with nonlinear ocean dynamics and quickly changing environmental variables, these methods frequently needed a lot of processing power and had poor forecasting accuracy, but they nevertheless produced useful predictions of wave height, period, and energy potential. Because of these restrictions, scientists have been looking at data-driven forecasting methods that can understand complicated connections from previous marine records.

Machine learning's (ML) ability to intelligently analyse massive oceanic datasets has greatly improved wave energy prediction. In terms of predicting major wave height, period, and energy generation, a number of supervised learning algorithms have shown encouraging results. These algorithms include Decision Trees, Extreme Gradient Boosting (XGBoost), Random Forests (RF), Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs). In contrast to traditional statistical models, these algorithms can automatically detect nonlinear correlations between weather factors, ocean characteristics, and past wave observations, leading to more accurate forecasts.

By successfully modelling complicated temporal and geographical connections within oceanographic data, recent breakthroughs in Deep Learning (DL) have considerably improved the accuracy of wave forecasting. The capacity of deep learning architectures like LSTM networks, CNNs, GRUs, and Transformer-based models to capture long-term temporal patterns and nonlinear wave behaviour has led to their widespread adoption for time-series prediction. Especially for jobs requiring medium-term and short-term wave prediction in very dynamic maritime settings, these models have shown to be better in terms of predicting ability.

The use of numerous deep learning and machine learning algorithms in a single hybrid or ensemble learning method has also been investigated by a number of academics. Improved prediction resilience, reduced forecasting errors, and enhanced model generalisation over varied ocean basins are all goals of hybrid forecasting frameworks, which incorporate complementary learning capabilities. In order to further improve dependability, ensemble approaches combine forecasts from many separate models. This reduces uncertainty and makes the forecasting more stable when faced with different environmental variables.

Table I. Summary of Existing Wave Energy Forecasting Techniques

Study	Methodology	Major Contribution
Numerical Wave Models	Physical & Statistical Modeling	Prediction of wave height and ocean conditions using mathematical models.
Machine Learning Models	ANN, SVM, Random Forest, XGBoost	Improved forecasting accuracy through data-driven learning.
Deep Learning Models	LSTM, CNN, GRU, Transformer	Captured temporal and spatial wave characteristics for enhanced prediction.
Hybrid & Ensemble Models	Combined ML and DL Techniques	Reduced forecasting errors and improved robustness.
Proposed Work	Comprehensive Review of ML, DL, Ensemble, and Hybrid Models	Comparative analysis of intelligent wave energy forecasting techniques and deployment through a Django-based forecasting platform.

There have been great strides, but intelligent wave energy forecasting still faces a number of obstacles. Predictive modelling is sometimes made more difficult by oceanographic datasets that include missing observations, measurement noise, seasonal changes, and very nonlinear environmental parameters. Important research difficulties include finding the sweet spot between accurate forecasts and efficient computing, choosing the best machine learning architectures, and making sure models can adapt to varied regions. The current study aims to review and analyse current methods of machine learning, deep learning, and hybrid forecasting in order to find effective ways to manage renewable energy sources and accurately predict wave energy.

III. PROPOSED WAVE ENERGY FORECASTING FRAMEWORK

The proposed system incorporates state-of-the-art methods for intelligent wave energy forecasting, including ML, DL, ensemble learning, and hybrid prediction algorithms. To reliably forecast SWH, wave duration, and wave energy potential, the framework is designed to examine past oceanic measurements, meteorological factors, and wave properties. The suggested methodology improves the dependability of numerical forecasts in the face of changing ocean conditions by using data-driven learning methods that can capture nonlinear connections and temporal dependencies in marine datasets.

Gathering historical oceanographic data from sources such as wave buoys, satellite observations, offshore monitoring stations, and meteorological organisations is the first step in the forecasting process. Significant wave height, period, wind speed, wind direction, air pressure, sea surface temperature, ocean currents, and other environmental factors that impact wave behaviour are usually included in the gathered information. These findings provide the groundwork for creating trustworthy machine learning prediction models that can understand intricate ocean dynamics.

In order to prepare the dataset for model training, data preprocessing is performed on the acquired information after data collecting. In order to enhance the dependability of forecasting, we manage missing data correctly, filter out noisy measurements, and delete inconsistent records. After processing, the dataset is turned into a structured format that machine learning algorithms can work with by normalising it. After that, in order to reduce computing complexity and duplicate information, feature engineering approaches are used to determine which oceanographic factors are most important for wave energy prediction.

A number of forecasting methods, including as ANNs, RF, XGBoost, CNNs, and Transformer-based architectures, are fed the optimised dataset. When it comes to ocean wave dynamics, deep learning models are better at learning long-term temporal dependencies and spatial features than traditional machine learning algorithms at capturing nonlinear interactions among environmental factors. In order to provide better predictions and make the model more resilient in varied maritime conditions, hybrid models incorporate complimentary learning skills.

Training the models with historical wave datasets and validating them with standardised experimental techniques ensures dependable predicting performance. Ratio of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are some of the most often used metrics in forecasting for comparative assessment. The precision of predictions, the stability of the model, and the dependability of forecasts under different ocean conditions are all thoroughly examined by these evaluation metrics.

Lastly, the forecasting findings are shown using interactive visualisation tools. These tools show the expected wave height, wave energy potential, historical trends, and performance comparison graphs. In order to optimise the operations of wave energy converters, improve renewable energy planning, and enhance marine safety via precise wave forecasts, these analytical studies are useful for researchers, offshore engineers, renewable energy suppliers, and maritime organisations.

IV. MACHINE LEARNING MODELS FOR WAVE PREDICTION

In order to reliably anticipate SWH, wave period, wave energy flow, and total wave energy production potential, the suggested wave energy forecasting system makes use of a diverse set of ML and DL models. Due to the nonlinear nature of ocean wave dynamics and the effect of many environmental factors, several learning techniques are used to capture the interplay of oceanographic parameters, including their temporal dependencies, spatial correlations, and complex interactions. By comparing and contrasting these models, we may find the forecasting methods that work best in different maritime environments in terms of prediction accuracy and computing efficiency.

When it comes to predicting wave energy, traditional ML techniques like ANNs, SVMs, RF, and XGBoost have shown excellent results. The nonlinear correlations between weather variables and wave features can be well-modeled by Artificial Neural Networks, and medium-sized datasets may be reliably predicted by Support Vector Machines using optimum hyperplane design. Combining several decision trees and minimising prediction variance, ensemble learning approaches like XGBoost and Random Forest further enhance forecasting dependability, making them appropriate for complicated oceanographic datasets.

By combining several Deep Learning architectures, the suggested approach enhances the performance of forecasting for sequential ocean data. If you need to forecast the height of a wave in the near or medium future, an LSTM network is a great choice since it can efficiently capture the long-term temporal dependencies present in past wave measurements. Regional wave forecasting in expansive maritime habitats is made possible by Convolutional Neural Networks (CNNs) that extract spatial patterns from oceanographic observations and satellite photos. In addition, as compared to traditional recurrent neural networks, Transformer-based models and Gated Recurrent Units (GRUs) both reduce computational complexity and effectively simulate long-range relationships, which enhances sequential learning.

Hybrid forecasting models, which integrate several ML and DL approaches to enhance prediction robustness, have recently shown efficacy in research. Oceanographic datasets may have their temporal and spatial information extracted using hybrid designs like CNN-LSTM, CNN-GRU, Prophet-LSTM, LSTM-Transformer, and Random Forest-XGBoost. These architectures combine complimentary learning capabilities. By improving generalisation performance across various geographical locations and environmental variables and minimising predicting mistakes, these combined models routinely beat separate methods.

The coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are some of the common metrics used to evaluate models in forecasting. Quantitative assessment of computing efficiency, model dependability, prediction stability, and forecasting accuracy is provided by these evaluation methods. According to recent research, hybrid deep learning models are better at modelling complicated ocean wave dynamics than standard machine learning techniques. This is shown by lower RMSE and MAPE values and higher R^2 scores.

Table II. Machine Learning Models for Wave Energy Forecasting

Model	**Primary Application**	**Major Advantage**
Artificial Neural Network (ANN)	Wave height prediction	Learns nonlinear relationships among oceanographic variables.
Support Vector Machine (SVM)	Wave forecasting	Effective for nonlinear regression and medium-sized datasets.
Random Forest (RF)	Wave energy prediction	High robustness and reduced overfitting through ensemble learning.
XGBoost	Ocean wave forecasting	Fast and accurate gradient boosting-based prediction.
Long Short-Term Memory (LSTM)	Time-series wave prediction	Captures long-term temporal dependencies.
Convolutional Neural Network (CNN)	Spatial wave analysis	Learns spatial patterns from satellite and buoy data.
Hybrid Models	Integrated wave forecasting	Combines multiple ML/DL techniques for higher prediction accuracy.

Furthermore, the comparative study shows that there is no one best forecasting model for all ocean circumstances. For highly nonlinear time-series data, deep learning and hybrid architectures give better forecasting accuracy, while traditional machine learning techniques provide efficient prediction with reduced processing needs. Therefore, the features of the dataset, the available computing resources, the length of the forecasting horizon, and the needs of the application are the primary factors to consider when choosing a forecasting model. As a result, renewable energy systems that include artificial learning algorithms provide a viable option for enhancing wave energy collection and bolstering sustainable power production.

V. PERFORMANCE EVALUATION AND COMPARATIVE ANALYSIS

A thorough comparison of current research on hybrid forecasting, ensemble learning, deep learning, and machine learning is used to assess the performance of the proposed wave energy forecasting framework. With the use of real-world oceanographic datasets gathered from wave buoys, satellite observations, offshore monitoring stations, and marine forecasting systems, this comparative analysis centers on the prediction of Significant Wave Height (SWH), wave period, wave energy flux, and renewable energy generation potential.

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2) are some of the often used evaluation metrics for conducting objective assessments of predicting effectiveness. MAE determines the average size of forecasting mistakes irrespective of direction, while RMSE quantifies the total prediction error by highlighting bigger variances. R^2 assesses the efficacy of the forecasting model in explaining variations in observed wave characteristics, while MAPE expresses prediction accuracy as a percentage, allowing comparison across datasets with different scales. The dependability of forecasts and the generalisability of the model are evaluated thoroughly by combining these performance indicators.

When it comes to predicting the behaviour of very nonlinear ocean waves, Deep Learning models often beat out more traditional machine learning methods, according to comparative assessment. The ability of Long Short-Term Memory (LSTM) networks to accurately capture long-term temporal relationships is what makes them so good for sequential time-series prediction. To enhance long-term forecasting, Transformer-based architectures represent complicated interactions within huge wave datasets, while Convolutional Neural Networks (CNNs) accurately extract spatial features from oceanographic observations and satellite images. When compared to more conventional statistical prediction approaches, these state-of-the-art designs drastically cut down on predicting mistakes.

In addition, the results show that out of all the methods tested, ensemble and hybrid forecasting models provide the best predictions. For more accurate predictions, use a hybrid framework that incorporates physical oceanographic models with other learning capabilities like as convolutional neural networks (CNNs), long short-term memories (LSTMs), generalised recurrent units (GRUs), random forests (RF), and XGBoost. The examined research show that R^2 scores are higher, RMSE and MAPE values are lower, and the models are more resilient and adaptable to different maritime settings. These results suggest better predicting accuracy. Thus, these combined methods work well for real-world wave energy prediction tasks that include intricate ocean dynamics.

The computational efficiency of real-time renewable energy applications is just as crucial as the accuracy of forecasts. In situations when ocean conditions are changing quickly, traditional regression-based models often use less computing resources but provide less accurate forecasts. The computational complexity of deep learning systems increases, but their predictive performance is better, whereas optimised hybrid frameworks strike a good compromise between the two. As a result, operational wave energy management systems may benefit from hybrid machine learning models, which provide a good balance between computational cost and forecasting dependability. It is clear from the comparison that intelligent machine learning approaches greatly improve wave energy forecasting when compared to more traditional numerical prediction methods. Sustainable power generation, offshore engineering, renewable energy planning, and efficient operation of Wave Energy Converters (WECs) are all made possible through the integration of deep learning, ensemble learning, and hybrid forecasting models, which allow for more reliable prediction of ocean wave characteristics.

VI. DJANGO-BASED WAVE ENERGY FORECASTING PLATFORM

The suggested wave energy forecasting framework is made more practical by incorporating machine learning models into a Django-based web app that allows for the visualisation, prediction, and monitoring of ocean wave characteristics in real-time. In order to provide reliable wave energy predictions, the online platform gives scientists, engineers specialising in renewable energy, and operators of offshore power plants a place to collaborate while studying oceanographic data. A user-friendly interface and smart forecasting algorithms work together in the suggested system to help with renewable energy planning and decision-making.

The application's backend is the Django framework, which handles tasks including user login, data upload, preprocessing, machine learning inference, result creation, and database operations. Historical oceanographic datasets may be uploaded by users. These records include environmental variables including air pressure, wind speed and direction, wave period, Significant Wave Height (SWH), and more. To ensure consistency with the training dataset used by the forecasting models, the uploaded data is preprocessed before prediction. This includes handling missing values, normalising the data, and extracting features.

Depending on the forecasting need, the optimised dataset is then sent to the specified forecasting model. That model might be Random Forest, XGBoost, LSTM, CNN, or a hybrid deep learning architecture. The engine that makes predictions uses the learned correlations in the oceanographic data from the past to make predictions about the height, duration, and energy potential of waves. With the help of an interactive dashboard, users can see the forecasted ocean conditions and assess the possibilities for renewable energy right now.

The developed dashboard presents comprehensive analytical reports through graphical visualizations, including wave height trends, forecasting timelines, prediction comparisons, error analysis charts, and renewable energy potential graphs. Users can compare various machine learning models and find the most reliable forecasting method for specific marine environments by viewing additional statistical reports that display forecasting performance using RMSE, MAE, MAPE, and R^3.

A centralised database is also a part of the Django app, and it safely keeps user data, trained machine learning models, forecasting reports, historical predictions, and user datasets. An administrative panel is available so that users can manage registered users, keep records of forecasts, update prediction models, and monitor the overall performance of the system. Furthermore, the modular system architecture allows future integration with IoT-enabled ocean sensors, real-time buoy monitoring systems, cloud-based renewable energy platforms, and smart grid infrastructures for continuous wave energy forecasting and intelligent power management.

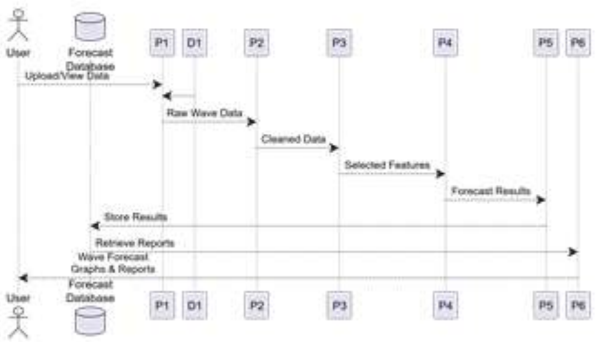

Fig. 1. Data Flow Diagram of the Proposed Wave Energy Forecasting System

VII. CONCLUSION

An extensive overview of Machine Learning (ML) applications for intelligent wave energy forecasting is provided in this study. The focus is on how these applications may enhance the prediction of ocean wave

characteristics and provide assistance for renewable energy systems that are sustainable. Predicting SWH, wave duration, and wave energy potential is the focus of this work, which examines a variety of forecasting techniques including hybrid models, ensemble learning, deep learning, and classic machine learning algorithms. The suggested framework shows how data-driven models may improve forecasting accuracy over traditional numerical approaches by analysing new advances in intelligent forecasting techniques and successfully capturing the complicated nonlinear behaviour of ocean waves.
Sequential ocean wave prediction is best handled by Deep Learning models like LSTM and CNNs, according to the comparison study. Ensemble learning techniques like XGBoost and Random Forest also help with forecasting robustness and reducing prediction uncertainty. Hybrid forecasting frameworks that include several machine learning methods also show better accuracy in predictions, less mistakes in forecasting, and greater flexibility to various ocean conditions. These intelligent forecasting systems promote renewable energy planning and dependable wave energy prediction, according to the assessment utilising RMSE, MAE, MAPE, and R^3.

The suggested framework is implemented as a Django-based web app that lets users execute machine learning prediction models, visualise forecasting results, and track renewable wave energy potential through an interactive dashboard. This makes the reviewed forecasting techniques more practical and user-friendly. Researchers, renewable energy developers, and offshore engineers now have a powerful decision-support tool at their fingertips thanks to the combination of web-based platforms and intelligence forecasting models. This tool will help them optimise the functioning of Wave Energy Converters (WECs) and improve sustainable energy management.

Incorporating real-time Internet of Things (IoT) sensor networks, ocean monitoring via satellite, deep learning architectures based on Transformers, Generative Adversarial Networks (GANs), machine learning guided by physics, and forecasting systems hosted in the cloud are all ways that future research might improve wave energy forecasting even more. Contributing to the sustainable utilisation of ocean wave energy resources, the integration of explainable artificial intelligence, digital twin technology, and smart grid communication platforms can enhance computational efficiency, forecasting reliability, and the large-scale deployment of intelligent renewable energy management systems.

REFERENCES

1. J. Yan, N. Mei, D. Zhang, Y. Zhong, and C. Wang, “Review of wave power system development and research on triboelectric nanopower systems,” Frontiers in Energy Research, vol. 10, Jul. 2022.
2. O. Farrok, K. Ahmed, A. D. Tahlil, M. M. Farah, M. R. Kiran, and M. R. Islam, “Electrical power generation from oceanic waves for sustainable advancement in renewable energy technologies,” Sustainability, vol. 12, no. 6, p. 2178, 2020.
3. C. Zheng et al., “An assessment of global ocean wave energy resources over the last 45 years,” Acta Oceanologica Sinica, vol. 33, no. 1, pp. 92–101, 2014.
4. P. M. G. M. Pinto, R. M. Campos, M. N. Gallo, and C. E. P. Ribeiro, “Predicting significant wave height with artificial neural networks in the South Atlantic Ocean: A hybrid approach,” Ocean Dynamics, vol. 73, no. 6, pp. 303–315, 2023.
5. X. Zhang, Y. Li, S. Gao, and P. Ren, “Ocean wave height series prediction with numerical Long Short-Term Memory,” Journal of Marine Science and Engineering, vol. 9, no. 5, p. 514, 2021.
6. A. Shadmani, M. R. Nikoo, A. H. Gandomi, R.-Q. Wang, and B. Golparvar, “A review of machine learning and deep learning applications in wave energy forecasting and WEC optimization,” Energy Strategy Reviews, vol. 49, p. 101180, 2023.
7. T. Breunung and B. Balachandran, “Data-driven, high-resolution ocean wave forecasting and extreme wave predictions,” Ocean Engineering, vol. 268, p. 113271, 2022.
8. [8] H. Wu, Y. Liang, and X.-Z. Gao, “Left-right brain interaction inspired bionic deep network for forecasting significant wave height,” Energy, vol. 278, p. 127995, 2023.
9. P. M. R. Bento, J. A. N. Pombo, R. P. G. Mendes, M. R. A. Calado, and S. J. P. S. Mariano, “Ocean wave energy forecasting using optimized deep learning neural networks,” Ocean Engineering, vol. 219, p. 108372, 2021.
10. N. C. S. Alfredo and D. A. Adytia, “Time series forecasting of significant wave height using GRU, CNN-GRU, and LSTM,” Jurnal RESTI, vol. 6, no. 5, pp. 776–781, 2022.
11. M. Ali and R. Prasad, “Significant wave height forecasting via an extreme learning machine model integrated with improved complete ensemble empirical mode decomposition,” Renewable and Sustainable Energy Reviews, vol. 104, pp. 281–295, 2019.
12. E. Tapoglou, R. M. Forster, R. M. Dorrell, and D. Parsons, “Machine learning for satellite-based sea-state prediction in an offshore wind farm,” Ocean Engineering, vol. 235, p. 109280, 2021.
13. F. C. Minuzzi and L. Farina, “A deep learning approach to predict significant wave height using Long Short-Term Memory,” Ocean Modelling, vol. 181, p. 102151, 2022.
14. A. M. Gómez-Orellana, D. Guijo-Rubio, P. A. Gutiérrez, and C. Hervás-Martínez, “Simultaneous short-term significant wave height and energy flux prediction using zonal multi-task evolutionary artificial neural networks,” Renewable Energy, vol. 184, pp. 975–989, 2021.

15. Q. Huang and Z. Cui, "Prediction of ocean effective wave height based on a hybrid artificial intelligence model," Ocean Engineering, vol. 289, p. 116137, 2023.
16. X. Huang, J. Tang, and Y. Shen, "Long time-series ocean wave prediction based on PatchTST model," Ocean Engineering, vol. 301, p. 117572, 2024.
17. J. P. D. Bieman, M. P. De Ridder, M. I. Mata, and J. C. C. Van Nieuwkoop, "Hybrid modelling to improve operational wave forecasts by combining process-based and machine learning models," Applied Ocean Research, vol. 136, p. 103583, 2023.
18. H. Hu, A. J. Van Der Westhuysen, P. Chu, and A. Fujisaki-Manome, "Predicting Lake Erie wave heights and periods using XGBoost and LSTM," Ocean Modelling, vol. 164, p. 101832, 2021.
19. D. Han and X. Xue, "Hybrid intelligent models for predicting weekly mean significant wave heights," Ocean Engineering, vol. 310, p. 118706, 2024.
20. M. Wang and F. Ying, "A hybrid model for multistep-ahead significant wave height prediction using an innovative decomposition–reconstruction framework and E-GRU," Applied Ocean Research, vol. 140, p. 103752, 2023.
21. P. Ramesh Babu, "An Intelligent Deep Learning Framework for Solar Power Generation Forecasting Using Weather Parameters," 2026.
22. P. Ramesh Babu, "Artificial Intelligence-Based Smart Energy Management System Using Machine Learning," 2026.