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Improving wave height prediction accuracy with deep learning

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ABSTRACT

A novel convolutional neural network-long short-term memory (CNN-LSTM) model is proposed for wave height prediction. The model effectively extracts relevant features such as wind speed, wind direction, wave height, latitude, and longitude. The proposed model outperforms traditional machine learning algorithms such as multi-layer perceptron (MLP), support vector machine (SVM), random forest and LSTM, especially for extreme values and fluctuations. The model has a significantly lower average root mean square error (RMSE) of 71.1%, 72.8%, 71.9% and 72.2% for MLP, SVM, random forest and LSTM, respectively. Our model is computationally more efficient than traditional numerical simulations, making it suitable for real-time applications. Moreover, it has better long-term robustness compared to traditional models. The integration of CNN and LSTM techniques improves wave height prediction accuracy while enhancing its efficiency and robustness. The proposed CNN-LSTM model provides a promising tool for effective wave height prediction, making a valuable contribution to coastal disaster prevention and mitigation. Future research should aim to improve long-term prediction accuracy, and we believe that the CNN-LSTM model plays a crucial role in developing real-time coastal disaster prevention and mitigation measures. Overall, our study represents a significant step towards achieving more accurate and efficient wave height prediction using machine learning techniques.

1. Introduction

Measuring nearshore waves is crucial for coastal protection and carrying out operations along the coast, such as harbour and dock design, flood protection measures, and economic development in coastal areas (Ardhuin et al., 2007). However, traditional observation methods require significant manpower and financial resources. Therefore, scholars both domestically and internationally have developed various models to simulate the propagation of nearshore waves. These models are primarily divided into semi-empirical models based on measured data and theoretical derivation (Young and Verhagen, 1996), and numerical simulation models based on numerical methods and software (Booij et al., 1999; Parker and Hill, 2017; Tolman, 1991).

In the past few decades, significant progress has been made in wave numerical simulation models based on the principles of wave dynamics and momentum conservation. Physically-based engineering wave forecasting models have been successively proposed, among which well-known ones include WAM (Komen et al., 1996), WAVEWATCHCIII (Tolman, 1991), and SWAN (Booij et al., 1999). These models have been widely applied in wave simulation (Samiksha et al., 2021; Zijlema, 2010), vegetation attenuation (Suzuki et al., 2012, 2019), storm surge modeling (Sebastian et al., 2014), and wave energy prediction (Lu et al., 2022; Ali et al., 2021), and other fields.

However, third-generation wave models require a large amount of computational resources and time to solve the equilibrium equation of wave action, and the computational efficiency and simulation accuracy cannot be considered for a long-term forecast of a region (Björkqvist et al., 2018). In recent years, with the improvement of concurrent computing performance of graphical computing devices, deep learning models have achieved rapid development in wave forecasting. Deep learning models can fit nonlinear relationships through the superposition of neurons and optimize parameters by back propagation, achieving high accuracy prediction of effective wave height (Malekmohamadi et al., 2011). In addition, the computation of deep learning benefits from the development of GPU with high computational efficiency. Therefore, deep learning can effectively balance the computational

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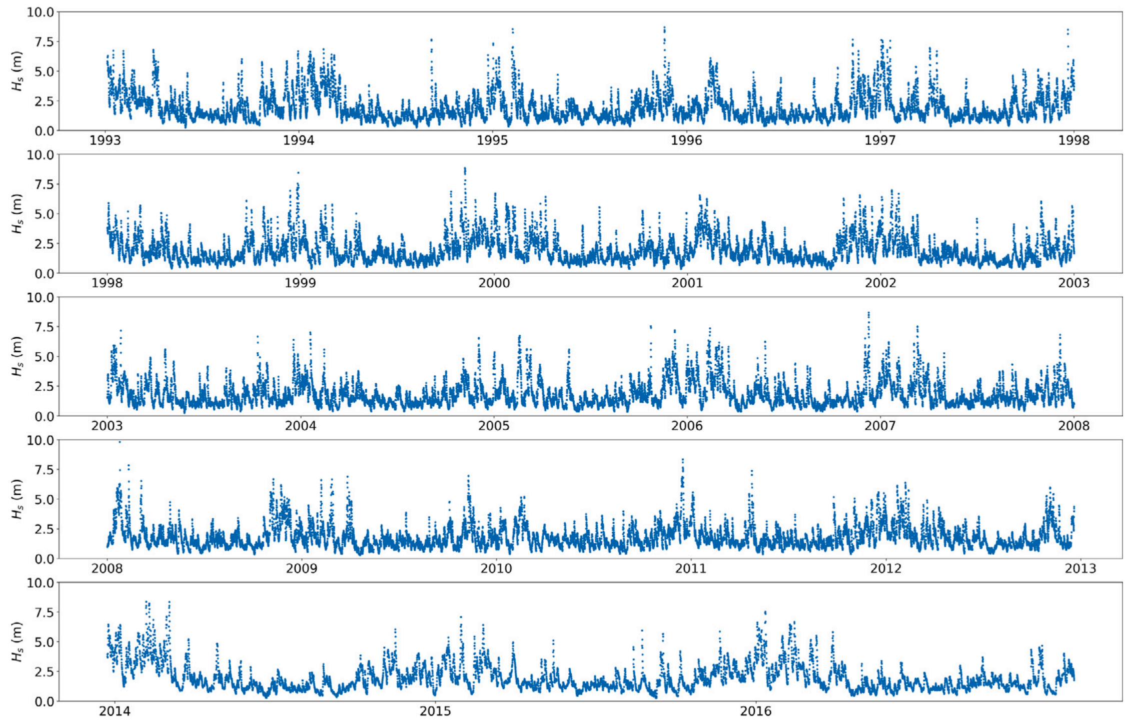

Fig. 1. Time series of wave parameters (H_s) from 2012 to 2016. The wave data were from ECMWF and National Marine Data Center respectively.

efficiency and accuracy problems. Deep learning has been widely applied to wave forecasting in the past decades. Rizianiza and Aisjah (2015) used backpropagation neural network to model and predict the effective wave height and wind direction data from two wave buoy stations near the Java Sea, where the root mean square error of one-hour forecast of effective wave height was 0.06 m and 0.07 m, respectively, with very high accuracy. James et al. (2018) proposed to predict the effective wave height using a multilayer perceptron SVM to identify the wave characteristic period. The model dataset consisted of wind data, effective wave height and SWAN simulation results. The results showed that the accuracy was higher using machine learning methods compared to SWAN simulation results. Feng et al. (2020) developed an MLP model to predict the significant wave height and peak wave period for Lake Michigan (Jing et al., 2022). The model takes into account topographic factors such as winter icing in Lake Michigan and has high prediction accuracy at less than one ten-thousandth of the computational time of the SWAN model. Ellenson et al. (2020) used WAVEWATCH III outputs as input features and the bias between modeling and observations as labels, and successfully reduced the predicted scatter index by 19%. Wang et al. (2022) integrated the physics-based SWAN model with BRT and ANN algorithms for predicting wind waves in a shallow estuary. The results indicate that this approach can effectively identify error sources and calibrate parameters, achieving results similar to field observations. Jing et al. (2022) developed a regional wave prediction model, CNN-RWP, based on convolutional neural networks (CNN) to establish the mapping relationship between wind data and wave data. The results indicate that the CNN-RWP model achieved an average absolute error of less than 10% compared to the output of the SWAN model, while improving computational efficiency by approximately 1000 times. Wang et al. (2023) employed a deep learning algorithm with a DAE model, achieving accurate coastal tsunami predictions based on actual sea observations for the first time, without the need for prior knowledge of tsunami sources or co-seismic deformations. Zhan et al. (2023) have developed a lightweight machine learning architecture called FreMixer for predicting non-stationary wave height time series. The research results demonstrate that FreMixer exhibits strong robustness in reducing deployment costs and improving training efficiency. Liu et al. (2023) employed a Vision Transformer-based model (VIT-RWP) for the prediction of regional significant wave height, achieving superior results compared to the conventional CNN-RWP model. This approach led to enhanced prediction accuracy and demonstrated remarkable robustness across diverse sea regions. Guan (2020) combined CNN and LSTM to achieve short-term wave height prediction for one month, but there is a lack of research on long-term wave forecasting.

Existing research mainly focuses on the use of different machine learning algorithms to predict short-term wave forecasts at a single point. However, the input of machine learning models based on numerical simulation results will lead to deviations due to the error of the simulation results themselves, and the data directly applied to the forecast may not be ideal (Londhe and Panchang, 2018). In addition, the wind field and wave field are two-dimensional fields. Therefore, predicting the wave height at a single point alone is only a time series prediction problem, and the influence of other surrounding points on the prediction point should be considered. In view of the above problems, this paper proposes to use CNN to extract the current and historical wind and wave feature information at different locations in the study area, improve the spatial wave information in the model prediction, and input the results into the LSTM model to establish a CNN-LSTM wave prediction model for achieving rapid and accurate prediction of significant wave height in the target area. Additionally, this study compares the CNN-LSTM model with four machine learning algorithms, namely MLP, SVM, Random Forest (RF) and LSTM, to analyze the model's robustness and adaptability.

This paper is organized as follows. Section 2 introduces and analyzes the datasets used in this paper. Section 3 introduces the basic theory and architecture of the CNN-LSTM model. This section also introduces some machine learning theories used in this paper. The analysis of CNN-LSTM model prediction results and the discussion of model robustness evaluation are introduced in Section 4. Section 5 expounds and summarizes the conclusions.

2. Materials

The wind field data were obtained from the ERA-5 reanalysis dataset of ECMWF (www.ecmwf.int) with a spatial resolution of 0.25° × 0.25°

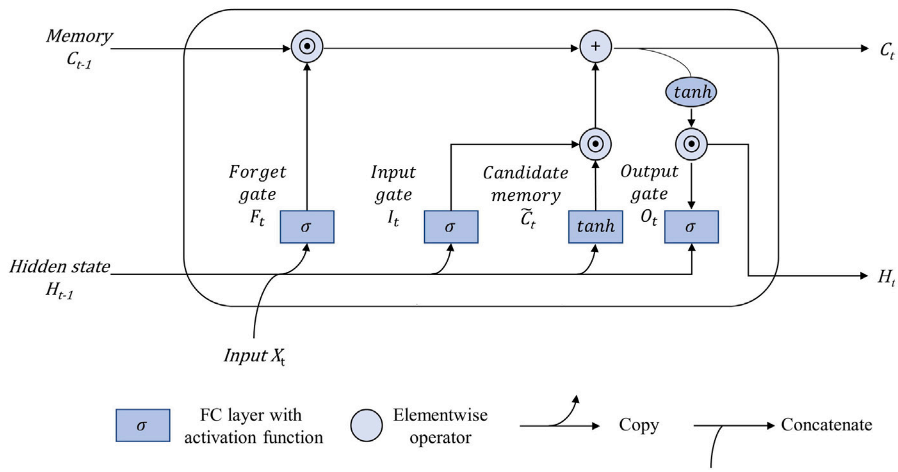

Fig. 2. Long short-term memory architecture.

and a frequency of 3 h per interval, covering the period from 1994 to 2016. The wave data were obtained from the ERA-5 reanalysis dataset of the National Oceanographic Data Center (http://mds.nmdis.org.cn/) and ECMWF. The study location was selected to be near the mouth of the Yangtze River (126°E, 30°N), taking into account the limitations of the dataset and ensuring the safety of navigation at sea. Fig. 1 displays the time series plot of significant wave height at the target location from 1994 to 2016. It can be observed from the time series plot that the wave data does not exhibit significant periodicity and is accompanied by some level of noise. The topography of the study area was derived from the ETOPO1 global terrain dataset (Amante and Eakins, 2009). The data used in this study can be obtained through the website mentioned above or from the GitHub repository at https://github.com/jackyvava/CNN-LSTM/tree/main.

3. Methodology

3.1. Relevant theories

Deep neural networks are an important and powerful branch of deep learning with the potential to construct more intricate network structures while improving feature extraction abilities. Compared to traditional neural networks, deep neural networks can perform non-linear transformations across multiple hidden layers, facilitating the handling of complex environments and problems (Yu et al., 2023; Mohammed and Kora, 2023). The prediction of wave height is of significant importance in the field of oceanography, as accurate predictions can aid in maritime safety, coastal planning, and climate research. In this study, a novel approach using a CNN-LSTM hybrid model was developed to predict the future wave height at a target point. Firstly, the collected wave height data was matrixized, and then inputted into the CNN layer. Here, the CNN layer used convolution kernels to extract spatial features related to the wave height, which were then compressed using a pooling layer to reduce overfitting. The parameters were finally passed into the LSTM layer for processing. By leveraging the strengths of deep neural networks, this CNN-LSTM hybrid model can effectively predict wave heights, offering numerous benefits over traditional neural network models, such as more accurate and efficient predictions. The proposed model can provide deeper insights into ocean dynamics, contributing to sustainable marine resource management. To ensure clarity, technical terms like "matrixization" and "overfitting" were defined throughout the article. Lastly, our literature review shows that the proposed model is competitive with existing methods and has the potential to enhance predictions in the field.

3.1.1. LSTM neural network

The LSTM (long short-term memory) algorithm, first proposed by Graves and Graves (2012), is a powerful tool for processing sequential data, making it a valuable asset for scientific research in numerous fields, including oceanography. For example, time series data for variables such as wave height, ocean temperature, and ocean currents are all instances of sequential data that can be processed using LSTM. To prevent the issue of long-term information preservation and short-term input loss commonly encountered with RNNs, the LSTM architecture integrates forgetting gates, input gates, and output gates into the hidden layer (Yan, 2015). These gates serve different purposes in controlling information flow in the network. Specifically, the input gate controls how much new information is passed on from the candidate memory element $\widetilde{C}_t$. In contrast, the forgetting gate controls how much information is carried forward from the previous time step's hidden state C_{t-1}, while the output gate manages how much of the present state is forwarded to the next time step (Hochreiter and Schmidhuber, 1997). The equations for calculating the input, forgetting, and output gates (Eq. (1)) demonstrate how the inputs from the current time step and the previous time step's hidden state feed into the gates to obtain their respective values. Following this, the multiple layers of the LSTM use the values of these gates to compute the final output of each time step (Eq. (3)). Fig. 2 illustrates the LSTM's structure, where H_{t-1} is the hidden state of the previous time step, and I_t, F_t, and O_t are the input, forgetting, and output gates for the current time step, respectively.

$$\begin{aligned} I_t &= \sigma\left(X_t W_{xi} + H_{t-1} W_{hi} + b_i\right) \\ F_t &= \sigma\left(X_t W_{xf} + H_{t-1} W_{hf} + b_f\right) \\ O_t &= \sigma\left(X_t W_{xo} + H_{t-1} W_{ho} + b_o\right) \end{aligned} \tag{1}$$

In the context of oceanography, the LSTM algorithm has been utilized as a valuable tool in many fields, including wave height prediction, ocean circulation modeling, and ocean temperature forecasting. For example, the LSTM's ability to capture the long-term dependencies in ocean data has enabled it to achieve accurate wave height predictions, crucial for marine safety and coastal planning (Zhang et al., 2018). Moreover, the LSTM has shown particular promise in forecasting the El Nino Southern Oscillation (ENSO), a vital driver of climate variability affecting ocean temperature and circulation (Wang et al., 2019). By using the input, forgetting, and output gates to regulate information flow, the LSTM model can capture complex patterns and dependencies

$$\widetilde{C}_t = tanh\left(X_t W_{xc} + H_{t-1} W_{hc} + b_c\right) \tag{2}$$

The result of this time step t can be calculated by elemental multiplication as follows:

$$C_t = F_t \odot C_{t-1} + I_t \odot \widetilde{C}_t \tag{3}$$

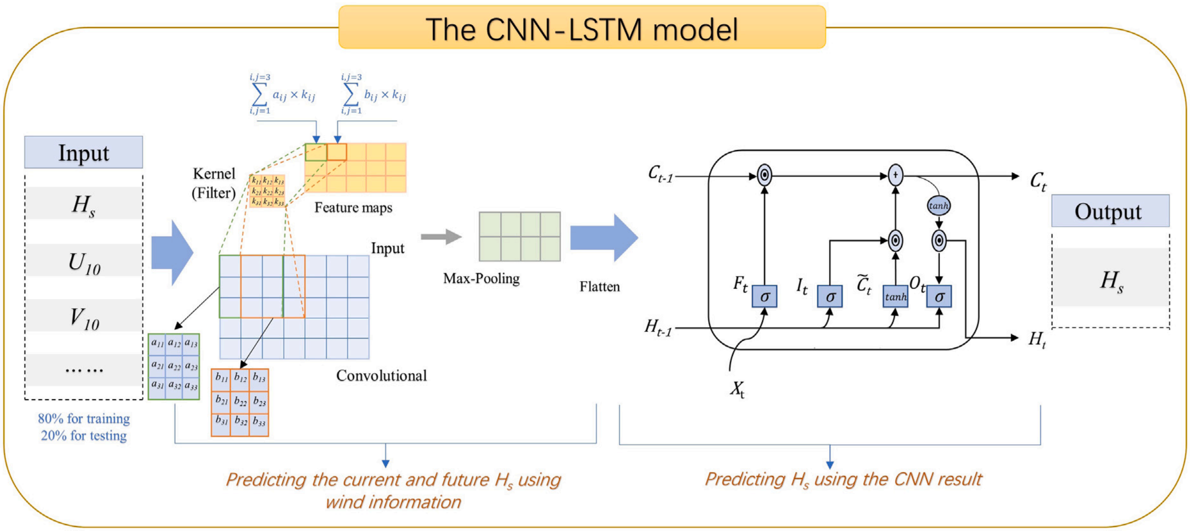

Fig. 3. Data processing flow of the CNN-LSTM hybrid model approach. Input includes data such as H_s, V_{10}, U_{10}, lon, lat, and so on.

where W_{xi}, W_{xf}, W_{xo}, W_{hi}, W_{hf}, W_{ho}, W_{xc} and W_{hc} are the weight parameters, b_i, b_f, b_o, b_c are the bias parameters.

3.1.2. Convolutional neural network

The Convolutional Neural Network (CNN) is a deep learning model renowned for its superior performance in matrix processing, and has been widely adopted across various fields including digital signal processing, artificial intelligence and machine learning (Jia and Sun, 2018; Can et al., 2021; Huang et al., 2022). Typically, a CNN model comprises layers including input layer, convolutional layer, pooling layer, fully connected layer, and output layer. In the present study, we utilized the convolutional layer and maximum pooling layer for feature extraction of wind field and wave height data center.

$$Y_j^k = f\left(k \sum_{i \in N_i} x_i^{k-1} u_{ij}^k + b_j^k\right) \tag{4}$$

where x_i^{k-1} is the output value of the ith feature map of layer$(k-1)$.

CNN performs a down-sampling operation on the input matrix to extract significant feature information from the input matrix. In general, the pooling layer comprises two types of operations, including maximum pooling and average pooling. The maximum pooling operation is used to replace the pooling region with the maximum value from that region, while average pooling, by contrast, replaces the region with its average value. The pooling layer plays an important role in expediting the training process while retaining crucial information. In this study, we utilized the maximum pooling method to reduce the dimensionality of the data, thereby reducing the number of parameters and complexity of the neural network.

$$P_{u,v}^{max} = \max_{i,j \in y_{u,v}} a_{i,j} \tag{5}$$

$$P_{u,v}^{aver} = \frac{1}{|y_{u,v}|} \sum_{i,j \in y_{u,v}} a_{i,j} \tag{6}$$

The fully connected layer is key to the CNN architecture, as it connects each neuron in the previous layer to all the neurons in the current layer. The fully connected layer shares the same structure as traditional neural networks and is typically used in the last few layers of a CNN. It integrates information transmitted from lower layers to obtain sophisticated feature representations of the image (LeCun et al., 2015; Jing et al., 2022).

3.2. CNN-LSTM model

3.2.1. Building the model

The CNN-LSTM algorithm flow is presented in Fig. 3, which illustrates the two main components of the CNN-LSTM short-term wave height prediction model. Specifically, the CNN extracts the corresponding feature sequence from the original time series data, while the LSTM network predicts the extracted feature sequence. Unlike traditional neural networks, the LSTM networks integrate a memory unit in the hidden layer to capture the long-term correlation within the time series (Hochreiter and Schmidhuber, 1997).

The model training process of the CNN-LSTM algorithm consists of two primary stages: forward propagation and backward propagation. During the forward propagation process, the loss function is employed to calculate the model error, which is defined as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) (see mathematical formula shown in Eq. (7)) (Guan, 2020; Zhang et al., 2021). In the backward propagation process, the adaptive moment estimation algorithm Adam is utilized for network parameter tuning (Kingma and Ba, 2014; Ruder, 2016).

$$L = \frac{1}{F} \sum_{T=1}^{F} \left(y_i - \widehat{y_T}\right)^2 \tag{7}$$

where y_T is the true wave height at moment T, $\hat{y}_t$ is the prediction report at moment T, and F is the number of samples in the training sample set.

The CNN-LSTM model constructed in this study is aimed at achieving accurate wave height predictions. The model's design is primarily grounded in physical theory, specifically the interaction between wind and the sea surface, which plays a crucial role in the generation and evolution of ocean waves. To effectively capture this physical process and address the challenge of long-term accurate forecasting, we incorporate key parameters such as current and historical wave heights, wind speed, wind direction, as well as longitude and latitude, into the prediction of current wave heights.

The core components of the model consist of CNN and LSTM. In the CNN model, multidimensional data are input, as depicted in Fig. 3, including historical wave heights, historical wind speeds, wind directions, and geographical coordinates (longitude and latitude). By employing 3x3 convolutional kernels, the CNN model efficiently captures spatial features within the data. Subsequently, we introduce the Rectified Linear Unit (ReLU) activation function to enhance non-linear representations and employ 2x2 max-pooling layers to reduce data dimensionality. Batch normalization is utilized to improve model stability

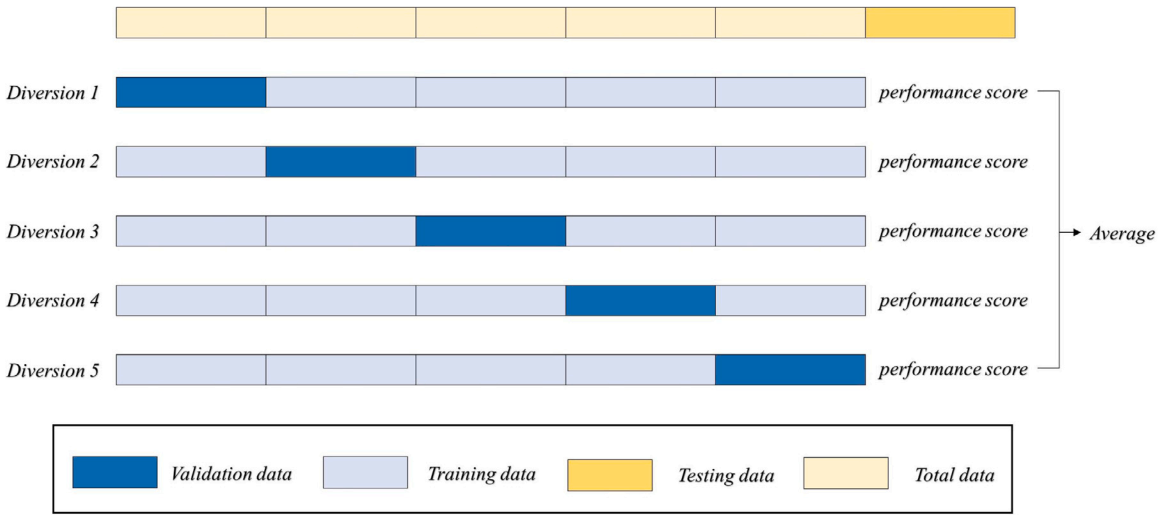

Fig. 4. The evanescent light - 1S quadrupole coupling ($g_{1,l}$) scaled to the bulk exciton–photon coupling ($g_{1,2}$). The size parameter kr_0 is denoted as x and the PMS is placed directly on the cuprous oxide sample ($\delta r = 0$, See also Table 1).

and expedite the training process. Finally, through the incorporation of a fully connected layer (FC layer), we map the feature maps extracted by the CNN to higher-dimensional representations. The feature maps obtained through the CNN serve as input to the LSTM network, which is specially designed for handling time-series data. We opt for 64 hidden units and set the batch size to 256 to capture temporal dependencies within the data.

The entire process of constructing the model takes into account multiple crucial factors, including historical wave heights, historical wind speeds and directions. Of particular significance is the incorporation of geographical coordinates in this model. This integration, in conjunction with the spatial information capturing capability of the CNN model, results in the establishment of a CNN-LSTM model that includes spatial information. Finally, model performance is assessed through K-fold cross-validation, ensuring the robustness and reliability of the model.

3.2.2. K discount cross-validation

Due to the limited number of data samples in this study, we employed the K-fold cross-validation method to select the optimal network parameters, as shown in Fig. 4. This method has been widely used in the literature to verify the selection of the optimal model from a range of models (Fushiki, 2011). In our study, we selected a K value of 5 to ensure that each set of training and validation data samples was large enough to be statistically representative of the broader dataset. We utilized data ranging from December 23rd, 2013 to December 28th, 2016 as the test dataset to evaluate post-training network performance. This portion of the data is referred to as the test set. The remainder of the dataset was divided into five subsamples, and for each structure, the network was trained separately five times, using a different subsample each time for validation. Based on the validation results of each structure, five performance scores were obtained, and the average score was used to represent the current grid's robustness (Wang et al., 2022).

3.2.3. Evaluation of predictive metrics

In order to quantitatively analyze the error of the forecast results, the coefficient of determination (R^2), root mean square error (MSE) and root mean square error ($RMSE$) are introduced to analyze the accuracy of the forecast results, and the calculation equations are shown in Eqs. (8), (9), (10), respectively:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(\hat{y}_l - y_i\right)^2}{\sum_{i=1}^{N} \left(\bar{y} - y_i\right)^2} \tag{8}$$

Table 1
Table for comparing errors of different models.

Algorithm	RMSE	R^2	MSE
CNN-LSTM	0.213	0.966	0.045
MLP	0.736	0.611	0.542
SVM	0.783	0.547	0.613
RF	0.759	0.574	0.575
LSTM	0.765	0.567	0.586

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_1 - y_i\right)^2} \tag{9}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{10}$$

where: $\hat{y}$ denotes the prediction result of the i test sample; y^i is the actual value of the i test sample; $\bar{y}$ is the average value; N is the number of test samples.

4. Results and discussion

The use of the CNN-LSTM method to predict effective wave height and experimental comparison with three popular machine learning algorithms – MLP, SVM, RF and LSTM – is presented in this study. The forecasting results of each model are depicted in Fig. 5. The comparison indicates that the CNN-LSTM model outperforms the conventional machine learning algorithms in wave height prediction, as evidenced by the smaller error obtained.

Table 1 displays the model error results, indicating that the CNN-LSTM model has higher accuracy when compared to the other four models. This is attributed to the proposed model's ability to extract important features from original wave height data through the convolutional and pooling layers, which improves the accuracy of the subsequent LSTM input data and retain data with a greater impact on prediction.

Due to the extended test set duration in this paper, detailed results cannot be displayed in the figure. Nonetheless, by selecting the time series of the first and last month of the forecast period, Fig. 6 highlights the effective short-term wave height trend forecasting capabilities of all models. It can be noted that the traditional machine learning model predicts extreme values poorly and has weak robustness for fluctuating regions. Unlike the traditional models, the newly constructed CNN-LSTM model displays more robustness for extreme values and

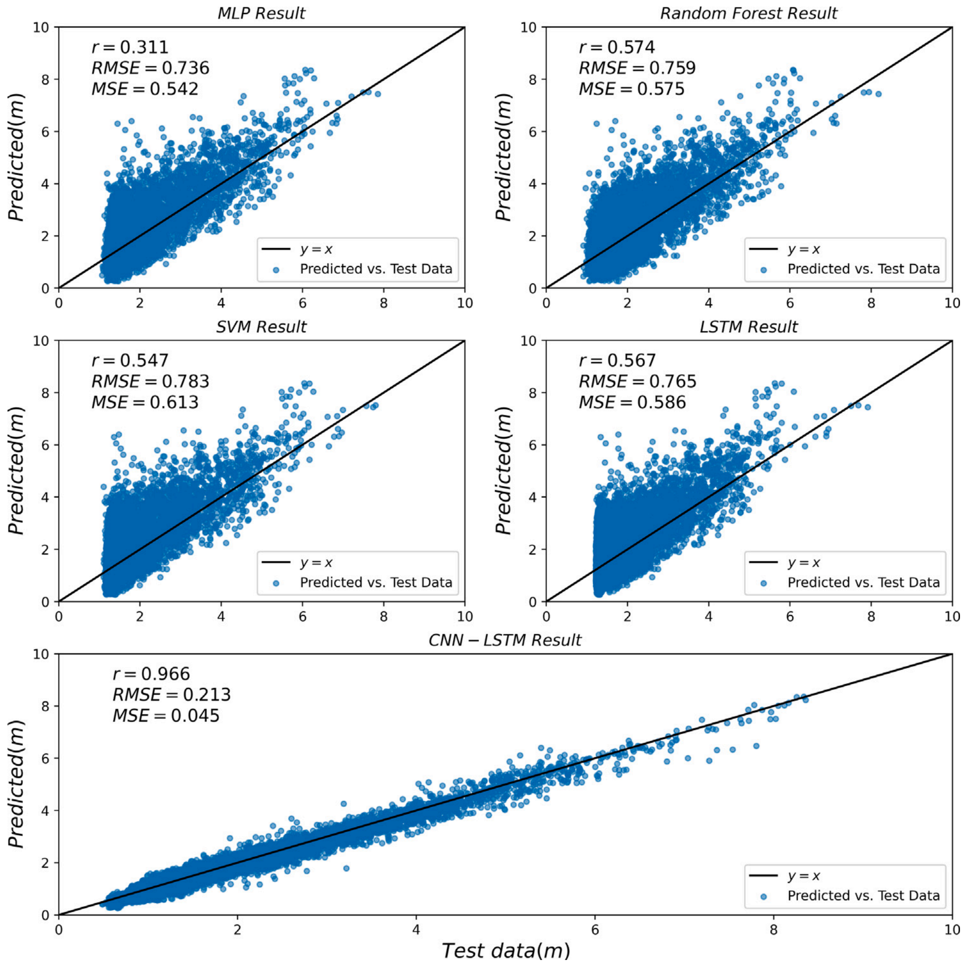

Fig. 5. Scatter plot comparison of model predictions and test data.

fluctuating regions while effectively forecast the extreme values of wave height, making it of significant value for coastal protection and wave forecasting.

The performance of the different models is compared as the forecast time extends in Fig. 6. For the first month of forecasting, all four models effectively forecast the trend of the effective wave height and captured extreme changes in the effective wave height. However, as the forecast time increases (measured on the right in Fig. 6), the conventional machine learning techniques such as MLP, SVM, Random Forest and LSTM, have poor forecasting results when contrasted with the CNN-LSTM model. The CNN-LSTM model displays better robustness as time increases, as long as the inputs' accuracy is guaranteed.

5. Conclusions

Managing wave disasters is imperative, and predicting effective wave height can provide better safety for coastal regions, maritime operations, and offshore constructions. Traditional wave forecasting methods are computationally intensive, while machine learning (ML) models have shown to perform better in various forecasting aspects. In this paper, a new hybrid deep learning model named CNN-LSTM with spatial awareness is proposed for accurate and faster long-term wave height predictions. The statistical reanalysis dataset ECMWF is utilized, and the model's results are compared with four other models, namely MLP, SVM, Random Forest, and LSTM.

The proposed spatial-aware CNN-LSTM model combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models for more accurate predictions of long-term wave heights. The CNN network extracts relevant information by identifying features from the reanalysis dataset, while the LSTM analyzes these specific features to generate a long short-term memory sequence for prediction. Compared to MLP, SVM, Random Forest, and LSTM models, the CNN-LSTM model demonstrates superior predictive capability. When evaluated using Root Mean Square Error (RMSE), it achieves an average RMSE value of 0.213, representing a reduction of 71.1%, 72.8%, 71.9%, and 72.2% compared to MLP, SVM, Random Forest, and LSTM models, respectively.

Additionally, through the analysis of time series from previous forecasts, it is concluded that the proposed model can more accurately predict wave height trends and better identify extreme points for short-term effective wave height forecasts. Furthermore, it is noteworthy that our proposed model exhibits superior robustness for long-term wave forecasting.

The results show that the proposed CNN-LSTM model can effectively and efficiently predict wave height, which is valuable in preventing and mitigating coastal wave disasters. Additionally, the model can support coastal authorities in issuing hazard warnings to better prepare for impending disasters. The model has lower computational requirements than traditional numerical simulations and runs approximately 1 h for a total running time on a 12-core Intel(R) 8255C CPU and 10 GB GPU. Traditional numerical simulations would require longer time to perform the same forecasting.

Future research work will focus on speeding up model training and combining numerical models with machine learning to improve the

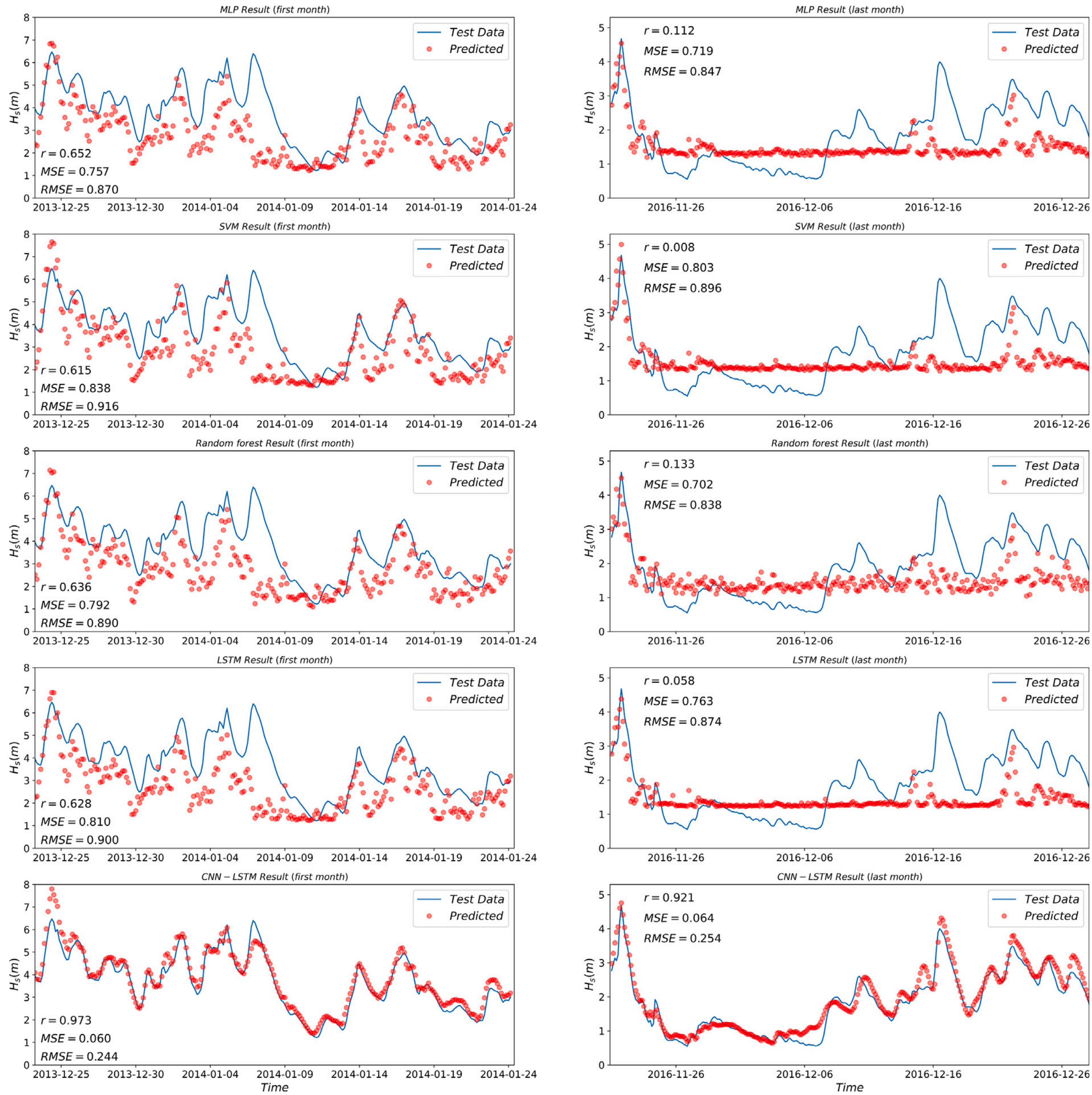

Fig. 6. Representation of predictions of H_s by different models on the test dataset, with the left column corresponding to the first month and the right column to the last month.

accuracy of long-term predictions. The results of this study demonstrate that the proposed CNN-LSTM model can provide valuable insights into wave forecasting, and its superior performance can lead to a more effective disaster management system.

In conclusion, it can be affirmed that the spatially-aware CNN-LSTM model exhibits the capability to provide more accurate and longer-term predictions of significant wave heights, thereby facilitating coastal disaster management. When the model forecasts extend beyond predefined thresholds, hazard warnings are issued, aiding authorities in better preparing coastal regions and maritime operations to mitigate potential disasters. As for future work, the research will focus on expediting model training speed and exploring comparisons and integration between physics-based and data-driven models.

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Computational library

The methods described in this paper are mainly divided into two categories. Among them, the traditional machine learning algorithms of SVM, MLP and Random Forest are implemented based on the Python language Scikit-learn library, which provides a variety of pre-built algorithms that can perform supervised and unsupervised machine learning. The library mainly includes classification, regression, clustering, dimensionality reduction, model selection and preprocessing walkthrough modules, including decision trees, support vector regression, multilayer perceptron, etc. The library resumes on top of Numpy, SciPy and Pandas and runs faster. The library can be run, validated, trained and tested on a single core. The MLP, SVR and Random classes are used in this paper, and the average running speed is less than 20 min. In addition, the TensorFlow library is used to construct the CNN-LSTM deep learning model, which can run on single CPU, GPU and large-scale distributed systems.

CRediT authorship contribution statement

Jie Zhang: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Feng Luo:** Funding acquisition, Project administration, Supervision. **Xiufeng Quan:** Investigation, Resources, Software. **Yi Wang:** Investigation, Software. **Jian Shi:** Investigation, Software. **Chengji Shen:** Formal analysis, Project administration. **Chi Zhang:** Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and code used in this paper are available at the following URL: https://github.com/jackyvava/CNN-LSTM/tree/main.

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