

Predicting one-day ahead wave heights using a hybrid model of long-short term memory and artificial neural network with resampling methods

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INTRODUCTION

In Japan, 1 m significant wave height (Hs) is treated as a threshold to make a decision of whether marine construction work for one week later can be carried out or not. Therefore, one-week-ahead wave predictions are critical. NOAA, JMA, and ECMWF forecast global wave information approximately one week ahead, while most marine construction work refers to nearshore wave observations (e.g., NOWPHAS) located along coasts. According to Hara et al. (2019), the accuracy of forecasted global wave heights is insufficient for making the decision for the nearshore marine construction.

In previous studies, many challenges were conducted to predict long-term ahead waves and surges. For instance, Kim et al. (2021) challenged one-week-ahead wave predictions using machine learning techniques. Kim et al. (2022) proposed a hybrid algorithm of combined long-short term memory (LSTM) and artificial neural network (ANN) to transform 24 hrs-ahead global waves to 24 hrs-ahead nearshore waves: LSTM predicts a time series of Hs for all Hs, and then ANN refines accuracies of Hs below 2 m that are predicted by LSTM. However, the accuracy of the hybrid algorithm was approximately 70 % to Hs = 1 m, which is the threshold of the marine work: its accuracy is still necessary to be improved for field managers who make the decision.

The present study challenges improving the accuracy of one-day ahead wave heights at Hitachinaka Port, Japan, by developing a framework of the hybrid model of LSTM and ANN with the resampling method to produce datasets for training and validating. In conclusion, the current model is able to predict 24 hrs-ahead wave heights with the normalized root mean square error (NRMSE) of 8.6 % and the correlation coefficient (CC) of 0.96.

METHOD AND EXPERIMENT

(1) Development of LSTM model

The LSTM model was developed by using datasets: the 513 daily wave data from 20th May 2019 to 30th January 2020 were collected for training and validating, while the 118 wave data from 3rd March to 30th April 2020 were used for testing. The best LSTM-based wave prediction model was optimized by investigating parameters of the epoch number, batch size, length, and dropout over three combinations of input data, JMA GWM and NOAA WW3, JMA GWM, and NOAA WW3, for instance. Once the parameters are optimized, the numbers of units (10 to 2000) and layers (1 to 8) are optimized. As a result, the combination of JMA GWM and NOAA WW3 was the best choice among the three potential datasets.

The LSTM model-predicted 24 hrs-ahead wave heights for testing are separated into two datasets: predicted and observed wave heights larger than 2 m and those smaller

than 2 m. The wave heights smaller than 2 m are used for datasets to train, validate, and test ANN models.

(2) Development of ANN models with inverse transform sampling

ANN-based models are developed using subsets created from the dataset smaller than 2 m by two resampling methods: inverse transform sampling (ITS) and simple random sampling with replacement (SRS). The inverse transform sampling is a pseudo-random number sampling to generate numbers at random from any probability distribution function (PDF) given its cumulative distribution functions. In the present study, 18 PDFs were investigated, resulting in the Kernel function being the best-fitted PDF by the goodness-of-fit tests of Kolmogorov-Smirnov (K-S) and Anderson Darling (A-D).

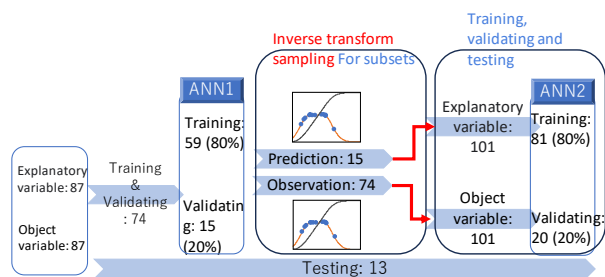


Figure 1 A flowchart of training, validating, and testing for developing the ANN-based model with the inverse transform sampling (number indicates the number of wave data)

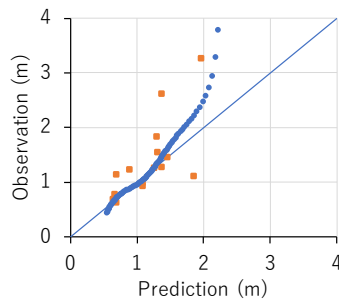


Figure 2 Comparisons of data: orange is predicted and observed data used for validating in the ANN1; blue is the subset data sampled by the Kernel function for training and validating in the ANN2

In this method, the ANN models were trained and validated, as shown in Fig.1. In the ANN1, 87 data are divided into three subsets: 59, 15, and 13 for training, validating, and testing, respectively. The test data are kept for each iteration. The 20 models are trained,

validated, and, tested. The tested 20 models are assessed by NRMSE and CC to decide the best performance model. In the 2nd iteration of ANN2, the subsets are sampled by the inverse transform method: explanatory variables for ANN2 are created using the 15 data predicted in validating by ANN1 (see Figure 2), while objective ones for ANN2 are produced by the 74 data in training and validating by ANN1. Then, those are separated into the two datasets of training and validating for ANN2. Repeatedly, the 20 models are trained, validated, and tested. Then, the best model is chosen by NRMSE and CC. If NRMSE and CC in the ANN2 are improved in comparison to those in the ANN1, the process continues. On the other hand, if those are not improved, the iteration stops. The best performance model in the ANN1 is an operation model in the field.

(3) Development of ANN models with simple random sampling with replacement

To develop ANN-based models, we implement the simple random sampling with replacement (SRS): In small populations and often in large ones, sampling is typically done "allowing replacement". In this method, we make the 10 subsets using SRS for training and validating. Then, 10 models are tested by the constant 13 data. The 10 tested models are assessed by averaging each CC and NRMSE (see Figure 3). Then, it is repeated 20 times, resulting in 20 averages of CC and NRMSE. As a result, the best performance model can be selected among 20 averaged CC and NRMSE.

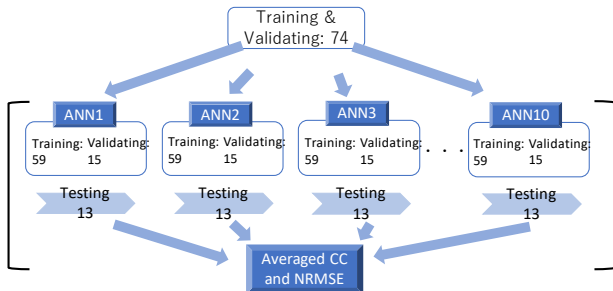


Figure 3 A schematic of resampling using the simple random method with replacement

RESULTS AND DISCUSSION

Of the ANN models with the inverse transform sampling, the best performance was found in the 1st iteration among the four iterations. The best one's CC and RMSE were 0.960 and 0.143 m, respectively (see Figure 4). Of the ANN models with the simple random sampling with replacement, the best one's CC and RMSE were 0.944 and 0.171 m, respectively (see Figure 4). As listed in Table 1, the ANN models with ITS showed 0.958, 0.145 m, and 8.58 % for the averages of CC, RMSE, and NRMSE, respectively. Those with SRS indicated 0.906, 0.211 m, and 14.68 % for the averages of CC, RMSE, and NRMSE, respectively. The ANN (ITS) revealed the best accuracy of 24 hrs-ahead Hs among the global wave forecasts and nearshore waves transformed by the ANNs. The results indicate that the model developed is able to predict Hs 24 hrs ahead with a higher accuracy of the error of 8.6 %.

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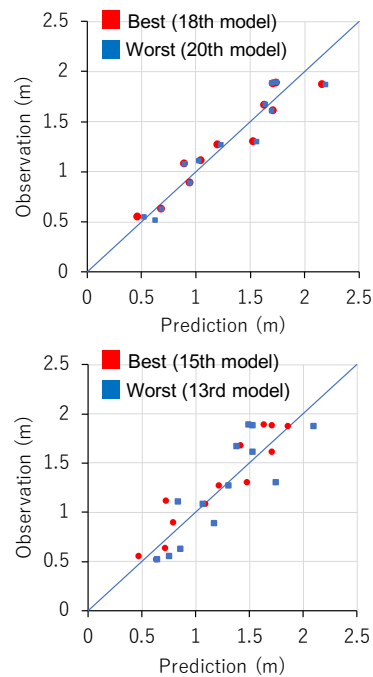


Figure 4 Comparisons of the best and worst models selected from two sampling methods (Upper panel: the inverse transform sampling and lower panel: the simple random sampling with replacement)

Table 1 Comparisons of wave prediction accuracies (All indices are an average of 20 models)

	CC	RMSE (m)	NRMSE (%)
JMA GWM (All)	0.506	0.796	10.48
NOAA WW3 (All)	0.478	0.889	10.51
LSTM (All)	0.902	0.379	11.07
LSTM (2m below)	0.815	0.328	23.11
ANN (ITS) (2m below)	0.958	0.145	8.581
ANN (SRS) (2m below)	0.906	0.211	14.68