INTRODUCTION
Forecasting of wave conditions plays an essential role for offshore construction and maintenance. At present, the real-time wave forecasting is mainly conducted by traditional numerical wave modelling, which can be computationally expensive and time consuming. Recently, machine learning-based wave forecasting models have been developed and their integrated usage with physics-based numerical models has become popular (O’Donncha et al. 2018). These studies mostly apply Feed Forward Neural Networks (FFNNs) with an emphasis on prediction of time-series of waves, tides and storm surges (Kim et al. 2016). However, FFNNs are related with vanishing and exploding gradient problems. As a particularly advanced approach, we develop a deep learning-based wave forecasting model using Long Short-Term Memory (LSTM) network under Recurrent Neural Networks. As a case study, the model will be utilized to predict the wave conditions (low or high) near the Tottori Port, Japan. The accurate prediction of low wave conditions is important for decision-making process of offshore and nearshore construction work. Therefore, the present model can be a practical tool to reduce the potential waste of resources in those projects.

METHODOLOGY
General framework of the model (Figure 1) includes input layer (to pass initial features from datasets), network layers (to conduct training/testing simulations) and output layer (to provide final classified forecast).

The input wave data is obtained from the Nationwide Ocean Wave information network for Ports and HArbourS (NOWPHAS) under the Port and Airport Research Institute, Japan. Hypothetically, the wave conditions are considered preferably low for working offshore if the values of significant wave height \( (H_s) \) and significant wave period \( (T_s) \) are smaller than 0.8 m and 9 s, respectively. Therefore, sequential information of \( H_s \) and \( T_s \) parameters are defined as input features. The output is the predicted wave classification results. Thus, the forecasted wave condition results can assist to determine whether it will be advisable or not to conduct work on the next day.

RESULTS AND DISCUSSION
The model simulations were conducted using input wave parameters \( (H_s \) and \( T_s \)) of i) one preceding day \( (24 \) h) and ii) two preceding days \( (48 \) h). Subsequently, the wave condition for i) \( 4 \) h, ii) \( 24 \) h, and iii) \( 24 \) h lead times were predicted. It was found that training and validation of the model with \( 48 \) h preceding input wave data results in higher accuracy than \( 24 \) h for forecasting of all lead times. The overall performance of the model for \( 48 \) h lead time is depicted in Figure 2, showing high validation accuracy (over 90%) with error (loss) values of around 0.12. Since the model counts as 1 for low wave condition and 0 for other, the confusion matrix shows the agreement of the predicted results with NOWPHAS observed data.

In summary, the results suggest that if the sequential wave data for at least \( 48 \) h is known, the wave condition (low or high) for \( 24 \) h lead time can be well predicted using the present model. Therefore, the present model can be used as an advanced tool to assist the planning of possible working days at offshore construction sites.

REFERENCES
Kim, Matsumi, Pan, and Mase (2016): A real-time forecast model using artificial neural network for after-runner storm surges on the Tottori Coast, Japan, Ocean Engineering,
122, pp. 44-53.