1. INTRODUCTION

In maritime activities such as maritime trade, the fishing industry, and ocean energy, are highly depending on ocean conditions, especially wave height conditions. Several factors may affect maritime activities, such extreme high wind that results in high waves, or cyclones that leads to very high waves. Especially for wave condition factor, an analyzable downscaling of ocean waves is indispensable in maritime activities to assist, reduce the possibility of accidents, and reduce thes likelihood of accidents and losses resulting from accidents due to sea conditions [1]. Accurate characterization of local or high-resolution wave climate is required. Wave climate is usually characterized by two sources of observations, buoys and satellites, and results from numerical models or dynamical downscaling. Buoys have the disadvantage of short records and significant gaps, while satellites provide global coverage but have only been available since 1992. Therefore, downscaling, such as dynamical and statistical downscaling, is an excellent alternative to performing high-resolution simulations [2].

To perform wave downscaling process, several numerical wave models have been employed by researchers, in the last three decades. For simulating wave height, especially in coastal areas, a spectral wave models Simulating Wave Nearshore (SWAN) is preferable for downscaling. Alizadeh et. al. [3] introduced a distributed wind downscaling method for modeling wave climate under future scenarios. This technique involves using a regional climate model (RCM) to simulate wind fields at various resolutions, followed by a statistical correction method to adjust wind speed and direction. The corrected wind fields are then utilized as inputs for the SWAN wave model to predict wave parameters such as significant wave height, mean wave period, and mean wave direction. The study assesses the method's performance by comparing simulated wave parameters with observations and other wave models for the present climate. Additionally, the technique is applied to project changes in wave climate for future scenarios (RCP4.5 and RCP8.5). The findings indicate that the method enhances wave simulations' accuracy and suggests significant future wave climate alterations, including higher waves and longer periods in specific regions. The study by Umesh [4] they evaluate input-dissipation parameterizations in WAVEWATCH III, a third-generation wave model. Comparing results with a nested WAVEWATCH III-SWAN model in the Indian Seas, it sheds light on wave prediction accuracy vital for maritime activities and coastal engineering. The paper likely provides detailed insights into parameterization effects, guiding optimal wave simulation settings in the Indian Seas. In Björkqvist's paper [5] where they compared WAM (Wave Action Model) with SWAN and WWIII. The WAM, among SWAN and WW3, is employed to simulate wave dynamics within Helsinki's coastal archipelago, utilizing a high-resolution grid and dual wind forcings. WAM exhibits favorable agreement with wave buoy measurements concerning significant wave height, showing minimal disparities in biases and root-mean-square-errors (RMSE) compared to other models. Notably, WAM tends to propagate long-wave energy more effectively into the archipelago, leading to heightened peak periods along the coast. These disparities mean peak periods between models can reach up to 1.4 seconds. However, WAM occasionally underestimates high-frequency wave energy under specific wind directions, potentially due to inadequate friction velocity. Furthermore, variations in the upper integration frequency contribute to biases in the mean period by approximately 1 second. While WAM effectively captures the spatial variability of the wave field within the archipelago, it encounters challenges in replicating temporal wave parameter variability. In a study by Martinez[6] it was explained that the dynamical downscaling approach requires significant computational power, while also demanding a large amount of data as input. The implementation of this technique also emphasizes the need for a high level of expertise to ensure proper and effective interpretation of the resulting simulation results. Through an in-depth understanding of these constraints, it is hoped that it will help in designing and implementing this method more efficiently in conducting ocean wave height simulations.

As a substitute for downscaling and enhancing earlier simulation models, machine learning has been applied extensively. For example, Kim [7] forecast one week in Hitachinaka Port, Japan, using six years of six-hourly data from the European Center for Medium-Range Weather Forecasts (ECMWF), National Oceanic and Atmospheric Administration (NOAA), and Japan Meteorological Agency (JMA). Kim employed the Group Method of Data Handling (GMDH) and Artificial Neural Network (ANN) as their two machine-learning techniques. Their work demonstrates that the machine learning framework for nearshore wave prediction may enable wave forecasts up to one week in advance and be applied areas where nearshore wave observation data is accessible. Another ANN model used for downscaling is Long short-term memory (LSTM). In a study conducted by Wei [8] two years of metrological data from NOAA were used to train the LSTM model on the Atlantic Coast of the United States demonstrates that Artificial Neural Networks (ANNs) are capable of functioning well and are free from overfitting and underfitting issues; short-term forecasts (one to six hours) yield more accurate results than long-term predictions (24 to 48 hours). In the paper of Adytia et. al. [9] using a more recent model, namely Bidirectional Long short-term memory (Bi-LSTM) with results with 14-day prediction results with a correlation coefficient (CC) score of 0.97, a RMSE score of 0.16, and a mean absolute percentage error (MAPE) score of 11.79. In the paper of Atiko & Adytia [10], they used the Transformers model to perform wave downscaling. Here, they able to get an accuracy of model with a CC performance of 0.96, a RMSE score of 0.16, and a MAPE score of 11.79. In Zhang's study [11] showed that the Temporal Convolutional Network (TCN) can outperform the LSTM model for forecasting in Traffic Flow. Wehage's study [12] compares machine learning models for weather forecasting, highlighting the TCN as a standout model. The TCN outperformed other models in six out of ten parameters when predicting weather conditions. This indicates its superior ability to effectively capture the nonlinear interrelationships among weather parameters and handle multivariate and sequential data. The TCN's architecture, which includes dilated convolutions, allows it to process long-range patterns and provides a significant advantage over traditional models that do not encode sequential information. The results suggest the TCN is a promising tool for accurate and fine-grained localized weather forecasting. In this research, we propose to model wave downscaling by using TCN model. We choose a case study at the coastal area of Bengkulu, Indonesia, in which its coastal area directly facing open Indian ocean. At this area, waves are dominated swell.

In this study, we suggested performing downscaling from a global grid using a machine learning technique in order to use the TCN to gain higher resolution. We train the TCN downscaling model using the spatial-temporal data of hourly waves in Bengkulu, Indonesia. By utilizing the SWAN model for spectral wave simulation, local wave height data are obtained by utilizing the global wave height data from ERA-5 (ECMWF). To get the best accuracy for downscaling using machine learning, we perform feature selection using a spatial correlation approach, in which we select the best location of wave global data as a feature for machine learning prediction, i.e., using TCN. Results of simulation are evaluated using CC, RMSE, and MAPE. Moreover, we also compare the results of TCN with the well-known Transformer and LSTM models. The aim of this research is to develop an improved model for simulating local wave patterns, which can be efficiently implemented in various locations across Indonesia with reduced computational costs and increased speed of the implementation of downscaling compared to traditional downscaling model. The following section describes the method used to perform the proposed machine learning downscaling approach.