I. Introduction

Many maritime activities, such as commerce and transportation, depend on the sea's condition, especially wave height. A reliable prediction of ocean waves can provide crucial information to avoid ship accidents and other losses [1]. Wave prediction in complex coastal areas, such as coastal areas, requires a more high-resolution or local approach. The downscaling technique increases the prediction scale from a global grid domain to a regional grid domain. Downscaling can be done in two ways: statistically and dynamically [2].

Numerical models have been used to simulate wave for their consistency with the physics of wave phenomena [3]. The popular third-generation numerical wave models are WAVEWATCH III (WW3)[4], WAve Model (WAM) [5], and Simulating Wave Nearshore (SWAN) [6]. There are still many issues when using numerical models, such as the requirement for large amounts of detailed geographic data and climate data, predictive accuracy is sometimes insufficient, and it takes a long time to get acceptable results when there is a large amount of data and complex computations [7], [8].

Machine learning has already been utilized as an alternative and improvement for numerical wave forecasting models. For example, Wei [9] used two years of meteorological data from four buoy stations belonging to the Administration NOAA or the National Oceanic and Atmospheric, on the US Atlantic coast to train a long short-term memory (LSTM) model. It showed that an artificial neural network (ANN) can work quickly and does not have the problems of overfitting and underfitting, and short-term predictions (1-6 hours) give more accurate results compared to long-term predictions (24-48 hours). However, only some have used machine learning to downscale ocean wave forecasting data. Machine learning-based downscaling for wave forecasting data have been used previously by Adytia et al. [10], using Bi-LSTM model with the results for the 14 days prediction were CC score of 0.97, RMSE score of 0.16, and MAPE score of 11.79.

We proposed a machine learning approach for wave forecasting data at global grid to obtain more high-resolution wave forecasting data using the Transformer model in this paper. The transformer model is used because it allows parallel computation, which enables faster and more scalable training [11]. We use spatiotemporal data for hourly waves in the Jakarta Bay area to train the transformer downscaling model. We take the global domain wave height data from ERA-5 (ECMWF) and obtain the local domain wave height data by implementing nested wave simulation on the global data using the SWAN model. We select features by comparing the spatial correlation of the input and the target data. We then implement the Transformer downscaling model, and finally, we evaluate the result by calculating the correlation coefficient (CC) value and the root mean square error (RMSE) value by comparing the Transformer high-resolution downscaling results with the SWAN high-resolution wave simulation results.