I. Introduction

Ocean wave dynamics are crucial for maritime activities, including tourism, engineering, fisheries, and transportation [1]. The increasing frequency of extreme wave events, such as rogue waves, poses significant risks by disrupting infrastructure and threatening livelihoods. Pelabuhan Ratu, Indonesia, located along the Indian Ocean, is particularly vulnerable due to its complex wave dynamics influenced by swell, local wind-driven waves, monsoonal wind patterns, and the Indian Ocean Dipole [2]. Contributing 70% of West Java's fisheries production and serving as a major transit hub [3], this region highlights the urgent need for reliable wave forecasting systems to enhance safety and inform decision-making.

Numerical models have traditionally provided accurate forecasts of ocean waves but are computationally intensive and struggle to address the inherent non-linearities of wave dynamics [4]. Deep learning methods, particularly Transformer-based architectures, have emerged as promising alternatives for time-series forecasting. These models excel at capturing complex temporal patterns, as demonstrated in influenza forecasting, where Transformer models achieved a Pearson correlation of 0.928 and a Root Mean Squared Error (RMSE) of 0.588 [5]. However, standard Transformer models face limitations in addressing seasonal variations and long-term dependencies, which reduce their effectiveness for wave height forecasting.

The Autoformer model offers a solution to these limitations by incorporating autocorrelation attention mechanisms and a multi-scale framework, enabling it to efficiently model non-stationary data [6]. Recent advancements, such as the Autoformer with De-Stationary Attention and Multi-Scale framework (ADAMS), have further enhanced its accuracy and efficiency [7]. For example, in photovoltaic power forecasting, the ADAMS model achieved a Mean Squared Error (MSE) of 0.061, an RMSE of 0.248, and an adjusted Coefficient of Determination (R^2) of 0.940, outperforming traditional models. These developments underscore Autoformer's adaptability for applications such as coastal risk mitigation and maritime operational planning.

This study evaluates the Autoformer model for wave height forecasting in Pelabuhan Ratu using wave height data generated through the Simulating Waves Nearshore (SWAN) model. The research compares Autoformer's performance with Transformer models across various forecasting horizons and addresses key gaps by analyzing advanced architectures for dynamic and non-stationary maritime environments.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on wave height forecasting, with a focus on time-series methods and deep learning models. Section 3 details the methodology, including data sources, preprocessing steps, and evaluation metrics. Section 4 presents the results, including a comparative analysis of the two models. Finally, Section 5 concludes with a discussion of the findings and offers recommendations for future research.

References

[1] X. Wu, R. Zhao, H. Chen, Z. Wang, C. Yu, X. Jiang, W. Liu, and Z. Song, "Gsdnet: A deep learning model for downscaling the significant wave height based on nafnet," *Journal of Sea Research*, vol. 198, p. 102482, 2024.

[2] D. N. Sugianto, M. Zainuri, G. Permatasari, W. Atmodjo, B. Rochaddi, A. Ismanto, P. Wetchayont, A. Wirasatriya *et al.*, "Seasonal variability of waves within the indonesian seas and its relation with the monsoon wind." *Indonesian Journal of Marine Sciences/Ilmu Kelautan*, vol. 26, no. 3, 2021.

[3] P. B. Maulana and A. Sawiji, "A study on the potential of electricity generation from wave energy in pelabuhan ratu, sukabumi," *Journal of Marine Resources and Coastal Management*, vol. 2, no. 2, pp. 6–10, 2021.

[4] Z. Bowei, G. Huang, and C. Wenjie, "Research progress and prospects of urban flooding simulation: From traditional numerical models to deep learning approaches," *Environmental Modelling & Software*, p. 106213, 2024.

[5] N. Wu, B. Green, X. Ben, and S. O'Banion, "Deep transformer models for time series forecasting: The influenza prevalence case," *arXiv preprint arXiv:2001.08317*, 2020.

[6] H. Wu, J. Xu, J. Wang, and M. Long, "Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting," *Advances in neural information processing systems*, vol. 34, pp. 22 419–22 430, 2021.

[7] Y. Huang and Y. Wu, "Short-term photovoltaic power forecasting based on a novel autoformer model," *Symmetry*, vol. 15, no. 1, p. 238, 2023.