iTransformer Application in Sea Level Forecasting: Case Study of Bali

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***Abstract*—The implications of sea level fluctuations, mostly attributed to global warming, pose significant challenges for naval operations, navigation, coastal economies, and infrastructure resilience. Accurate sea-level prediction is vital to mitigate these challenges, particularly in areas prone to tidal flooding and infrastructure damage. This study introduces a cutting-edge deep-learning model, iTransformer, for sea level prediction, utilizing six months of data with four months allocated for training and two months for validation and testing. The dataset used originates from Singaraja, Bali, Indonesia, and projects sea levels over a 14-day timeframe. Our findings reveal that iTransformer outperforms both Temporal Convolutional Networks (TCN) and Transformer models in terms of prediction accuracy and has a significant amount of short-term computational efficiency. iTransformer achieves the prediction score with an RMSE of 0.0041 for the 24-hour, 0.0415 for the 48-hour, and 0.0455 for the 96-hour. MAE of 0.0489 for the 24-hour, 0.0323 for the 48-hour, and 0.0368 for the 96-hour, and R^2 scores of 0.9713 for the 24-hour, 0.9882 for 48-hour, and 0.9863 for the 96-hour prediction windows, respectively. Furthermore, iTransformer demonstrates lower computational times, requiring only 0.1 minutes for a 24-hour window and 0.3 minutes for a 48-hour window. These results underscore iTransformer's potential as a robust model for sea level prediction and indicate that its application could be extended to multivariate datasets to enhance performance.**

***Keywords*—Sea level forecasting, iTransformer, MAE, RMSE, R2**

I. Introduction

The caused of sea level is usually affected by gravitational causes such as the Earth, Moon, and the Sun to the sea level resulting in the sea level changing. The phenomenon is called the tide effect and usually, it is the result of the formation of two high tides and two low tides each day as the Earth rotates to the moon position. Additionally, sea level rise primarily caused global warming that poses a threat to the sea level changes. According to the SROCC report Chapter 4, sea levels are projected to continue rising at an accelerated pace, potentially reaching up to 1 meter by the year 2100 [1], [2]. Research and experiments have been conducted in several years particularly involving traditional approaches to analyze the specific amplitude and frequencies of the sea levels resulting in the Tidal Harmonic Analysis (THA) approach [3].

The limitation posed by the THA method is the requirement of a long range of time-series sea level data. To mitigate this issue, sea level forecasters need to analyze present conditions and mitigate the future impacts of the sea level changes [4]. Further research has explored in the different approaches of the time-series forecasting model for predicting sea levels, including the notorious model of the Long Short-Term Memory (LSTM) [5]. Also, recently the Transformer which is known for its capability in handling semantic tasks in NLP and CV, has been used in time series forecasting [6], and the recent durable model the TCN [7].

In [6], the author concludes that while the Transformer model incurs higher time complexity in terms of computing time compared to other models, its efficiency is largely attributed to its unique architecture. Specifically, the Transformer's ability to parallelize the attention mechanism significantly reduces the overall complexity. This parallelization enables the Transformer to process time-series data more effectively by focusing on different parts of the sequence simultaneously, rather than sequentially as in traditional models. This capability allows for faster training and inference times, making it particularly advantageous for handling large-scale time-series forecasting tasks where capturing long-range dependencies and patterns is crucial.

Other approaches from TCN are particularly well-suited for time-series forecasting due to their ability to handle sequential data effectively. Unlike traditional RNNs that process sequences step-by-step, TCNs leverage a fully convolutional architecture, allowing for parallel processing of entire sequences. This results in faster training and inference times. TCNs use causal convolutions to ensure that predictions respect the temporal order of the data, and dilated convolutions to capture long-range dependencies without a significant increase in computational cost. Additionally, residual connections within TCNs help mitigate the vanishing gradient problem, enabling the training of deeper and more robust models.

In this paper, we will use a novel deep-learning model called the iTransformer introduced by Liu et al. in 2023 [8]. The explanation of iTransformer will be described in Section II. The content of this paper is as follows. First, we will discuss the literature or any related work that has been made by other authors on the related field of study, specifically about the new model of iTransformer in Section II, then followed by a description of the iTransformer model in Section III. In Section IV, we will discuss the results of iTransformer, and

