TABLE I: Performance Comparison Between Models for Different Lookbacks

Model	Lookback	RMSE	MAE	R^2	C.T. (min)
iTransformer	24	**0.0041**	0.0489	0.9713	0.1
	48	0.0415	**0.0323**	**0.9882**	0.3
	96	0.0455	0.0368	0.9863	0.36
TCN	24	**0.1050**	**0.0862**	**0.9861**	3.3
	48	0.1227	0.1006	0.9810	2.3
	96	0.1172	0.0933	0.9827	1.88
Transformer	24	0.0410	0.0331	0.9886	5.05
	48	0.0409	0.0325	0.9883	12.1
	96	0.1285	0.1033	0.9792	19.8

Table I compares the performance of iTransformer, TCN, and Transformer models for lookbacks of 24, 48, and 96. The performance metrics include Root Mean Squared Error ($RMSE$), Mean Absolute Error (MAE), R-squared (R^2), and $C.T.$ representing Computing Time. The bold values indicate the best performance for each metric.

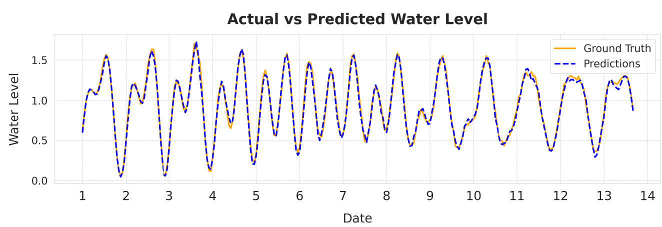

Fig. 6: iTransformer 14-days Actual and Prediction Data.

V. Conclusion

We presented sea level forecasting using a novel deep-learning approach called iTransformer with short-term data, specifically six months, utilizing four months for training and the remaining two months for validation and testing. The iTransformer model predicts sea levels over 14 days. As a case study, we used a dataset from Singaraja, Bali, Indonesia. Based on our experiments, it can be concluded that iTransformer achieves the highest prediction accuracy, surpassing both TCN and Transformer models. Additionally, the iTransformer model exhibits lower computational times, requiring only 0.1 minutes for a 24-hour lookback, 0.3 minutes for a 48-hour lookback, and 0.36 minutes for a 96-hour lookback.

We also discovered that a 48-hour lookback period yields high accuracy for the iTransformer model, with an RMSE of 0.0415 and an MAE of 0.0323, both of which are very low. This is complemented by R^2 scores of 0.9882, which indicate strong predictive performance but compared to the other models, iTransformer excels in short computational time. The results of the iTransformer model may serve as a foundational basis for future iterations of the iTransformer as a forecasting model. It is important to note that multivariate datasets are highly recommended, as iTransformer is designed for multivariate analysis, whereas this study employed univariate datasets.

Limitations and Future Works

Our tests were conducted on univariate and short-term datasets, while iTransformer is designed to excel with long-term multivariate datasets. We suggest further research and improvement are necessary to fully evaluate and implement iTransformer with multivariate features. We sincerely hope our comprehensive studies can benefit future work in this area.

iTransformer possesses various advantages and disadvantages. Nonetheless, it offers extensive opportunities to explore, reproduce, and implement long-term multivariate datasets.

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