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Predicting tidal level in tropical Eastern Bintan waters using residual long short-term memory

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ABSTRACT

The sea brings many benefits for society, especially for a maritime country such as Indonesia, and the potential in various sectors is limited only by the willingness of a party to invest in it. Using a residual long short-term memory (LSTM) algorithm, we will predict the tidal level in Eastern Bintan Island. The dataset is acquired from two sensor points in eastern Bintan coast from July 2018 to June 2019 for a span of one year, giving a total of 7,961 data points. The residual LSTM model consists of a residual wrapper with two consecutive LSTM layers and one dense layer. The model is also compared with variations of LSTM and recurrent neural network (RNN) models. The result of the residual LSTM model has a mean absolute error (MAE) value of 0.1495 cm and a root mean squared error (RMSE) value of 0.3353 cm, compared to the baseline model's 1.1148 cm and 1.4107 cm respectively. The model also has an RMSE value improvement of 76.23% compared to the base model.

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1. INTRODUCTION

The abundance of natural resources and the strategic value of the sea brings many benefits for the society around it. This is especially true in maritime countries with a large sea area, such as Indonesia. As the largest archipelagic country in the world with many straits and strategic positions in its territory, Indonesia has the potential to become a global powerhouse, provided that they use the abundance of the sea to its full potential.

Indonesia is currently still lacking in its maritime sector compared to other archipelagic and maritime countries. This lag in the maritime sector can be attributed to a lack of usage and development of sophisticated advanced technology, lack of infrastructure and integration of its many islands, and the inability to reform its traditional products from the abundant natural resources [1]. Better port infrastructures and a more refined connectivity between major and minor islands is critical to improve the situation [2]. The creation of new mineral refineries and education for capable workforce is also a way to harness the abundant natural resources and improve the economy [3].

For sophisticated and advanced technology to be widely used and frequently improved, a large and steady amount of data is needed to support it, as technology relies on data for its operation [4]. Research and innovation for digital technologies in the maritime industry has been done for the past few years, with promising new technologies that could reshape the maritime supply chains if the infrastructure and data is available [5]. The implementation of big data and artificial intelligence technology to maritime industry will improve technology usage and allow for further technological research, from surveillance and data collection to logistical and route planning [6].

One such use of big data and artificial intelligence is the ability to analyse and predict future sea situation from the data collected in the past. Prediction is especially important because having an accurate prediction of the condition will allow for a better judgement and planning, such as in ship routings [7] and coastal cities disaster prevention [8]. However, while large scale industries have adopted at least some kind of prediction in its operation, more than half of small scale and local fisherman still opted for traditional knowledge instead of scientific predictions [9].

Many aspects of the sea can and has been predicted by many researchers, such as the sea surface temperature [10] and ocean weather [11]. One of the aspects that is important to predict is the tide level, as it affects various sectors, particularly those that frequently embark and disembark from the coast. Fishermen would time their departure, fishing duration, and return based on the tidal level [12], transport ships are affected by tidal level and need to schedule when they docked into port [13], and microplastics in some coastal areas have a concentration pattern that is related to the tides [14], [15].

Since tides are related to time, it can be predicted using the time series forecasting method. While traditionally a simple harmonical analysis is used to give a good approximation, nowadays the usage of artificial intelligence is preferred because of better results and tides prediction is a perfect use case of artificial intelligence [16]. Machine learning and deep learning allows for machines to learn and understand large amounts of data like how humans think, even from various unstructured data [17].

One such method that can effectively learn the pattern of a time series is long short-term memory (LSTM), a type of recurrent neural network (RNN) that is better at long-term dependencies than its standard counterpart [18]. Therefore, this study intends to employ an LSTM solution to predict tidal levels using data acquired on Bintan Island, an island located on the Riau Islands archipelago in Indonesia. The architecture is expected to accurately predict the tidal levels for the next 24 hours using the previous 24 hours as reference.

2. RELATED WORKS

LSTM is an algorithm that is already widely used in various fields of study and has been extensively used in deep learning. Research about tidal level and other sea conditions has also been done by multiple researchers. This study is inseparable from previous research as a reference, and listed here are some that inspired the writing of this paper.

Yang *et al*. [19] predicted the tidal level in 17 harbors in Taiwan using seven different algorithms and picking the best one. The algorithms used are autoregressive integrated moving average (ARIMA); support vector regression (SVR); trigonometric seasonality, box-cox transformation, autoregressive moving average errors, and trend seasonal components (TBATS); particle swarm optimization support vector regression (PSOSVR); artificial neural network (ANN); convolutional neural network (CNN); and LSTM. Out of them all, LSTM had the lowest mean absolute percentage error (MAPE) and root mean squared error (RMSE), with 6.97% and 0.049 m respectively.

Balogun and Adebisi [20] predicted the sea level in West Peninsular Malaysia by combining various ocean-atmospheric variables and picking the best algorithm between ARIMA, SVR, and LSTM. They found that LSTM outperformed the other algorithms when using the various variables. But noted that ARIMA excels where tidal influence is strong without accounting for the other ocean-atmospheric variables.

Bai and Xu [21] predicted the tidal level on 5 tidal stations in USA's east coast. The proposed method uses the bidirectional long short-term memory (Bi-LSTM) algorithm to predict short term tidal level in both single-step and multi-step. They found out that Bi-LSTM has excellent capability in predicting short term tidal level for single-step and multi-step prediction compared to traditional methods such as harmonic analysis, backpropagation, radial basis function (RBF), and extreme learning machines (ELM).

Mathew and Abdulla [22] predicted the quantity and spending demand of e-procurement in the hospitality industry within the United Arab Emirates (UAE). They used an LSTM model with 8 layers and 500 epochs and trained it based on five years of historical data acquired from a hotel chain in UAE. The model was able to predict the spending and order amount with an RMSE value of 0.0137, compared to the baseline RMSE value of 9221.876.

Ewees *et al.* [23] predicted the wind power on four wind turbines in France using 5 different algorithms and picking the best one. The algorithms used are heap-based optimizer (HBO)-LSTM, LSTM, ANN, support vector machine (SVM), and generalized autoregressive conditional heteroskedasticity (GARCH). Out of them all, HBO-LSTM has the best performance, followed by LSTM, SVM, GARCH, and ANN respectively.

Yuniarti *et al*. [24] predicted the electrical load of Indonesian power grid using 1 to 3 layers of LSTM for comparison. Based on an hourly historical data between 2013 to 2017, they were able to predict the electrical load demand for the next 24 hours. The result shows that models with more LSTM layers perform better than those with less LSTM layers, with a MAPE value of 8.63% for the 3 LSTM layers model, whereas the 2 layers and 1 layer have a MAPE value of 9.04% and 9.29% respectively.

3. METHOD

Using the LSTM algorithm, the proposed prediction model would predict the tidal level for the next 24 hours in a one-hour interval, using the previous 24 hours historical data as reference. This would give an ample amount of predicted timeframe while maintaining a high level of accuracy. LSTM is used for this research because it offers the best use when it comes to time series forecasting, and past research has shown that LSTM is superior when compared to other algorithms for time series forecasting purposes. The proposed method used for the construction, as seen in Figure 1, of the prediction model can be described as follows:

- Dataset acquisition: the dataset is acquired from the head researcher of a project by the Faculty of Marine Science and Fisheries as part of a collaborative effort with the Faculty of Engineering and Maritime Technology. The dataset consists of 20 months of historical tidal level data, for a total of 11,846 data points.
- Dataset preparation: the dataset is opened in Excel for initial analysing. Upon further analysis, some period of data is missing from the dataset, likely because of sensor maintenance. The longest uninterrupted period is used for training purposes, while the rest are discarded. The dataset is then cleaned and reformatted to fit with the TensorFlow program.
- Dataset segmentation: the dataset is segmented into a training, validation, and test set. The dataset is not shuffled before segmentation because of the nature of time series data. The segmentation ratio for training, validation, and test set is 70%, 20%, and 10% respectively.
- Baseline modelling: a baseline model is created for comparison purposes by shifting the data to the next 24 hours for its prediction, a method that is considerably effective on its own already given the nature of the dataset. The performance of the baseline model will be used to compare the effectiveness of the prediction model.
- Model tweaking: the models are tweaked to find the best performance result by modifying the structure and composition of layers, trainable parameters number, epochs amount, optimizer used, and metrics used.
- Model training: the models are trained, and their performance results compared with the baseline model and their previous models. If further improvement can be made, the parameters are tweaked again before retraining the models. Once no further improvement is made, the best model is saved while the rest are used for comparison purposes.

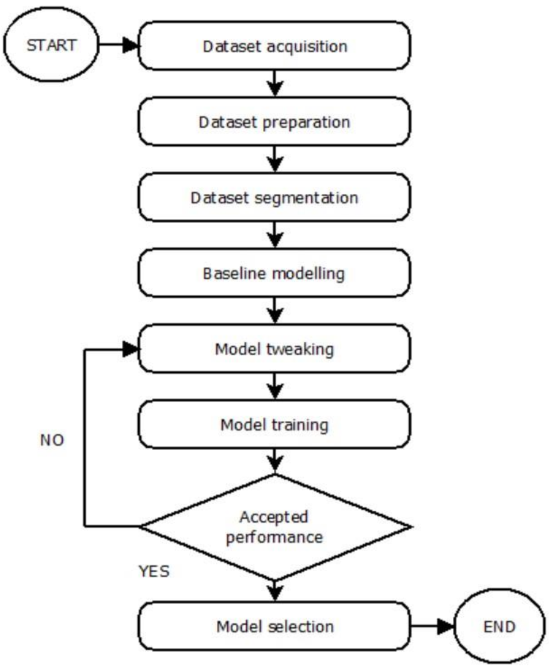


Figure 1. Proposed method for tidal level prediction

3.1. Dataset

The raw data used for this research is gratefully given to us by Raja Ali Haji Maritime University's Faculty of Marine Science and Fisheries, and can be accessed from the research by Apdillah *et al*. [25]. Tidal level data collected from the sensors are compared with data from the Indonesian Geospatial Information Agency or Badan Informasi Geospasial (BIG), with an R2 value of 0.83 and P value <0.05, thus the performance of the sensor is scientifically justified. The data is collected from 2 points in Bintan, an island near Singapore that is part of an archipelago located on the tip of Malay peninsula, from July 2018 until January 2020 for a total of 20 months as seen in Figure 2. Unfortunately, a long maintenance period is done between June and July of 2019, as well as some shorter maintenances around December 2019 and January 2020. To ensure a clean pattern for training, we decided to only use the data on the longest uninterrupted segment, from July 2018 to June 2019, for a total of 7,961 data points.

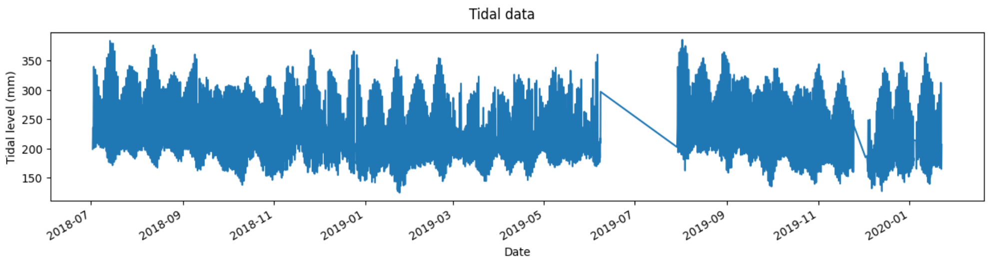


Figure 2. Tidal data between July 2018 and January 2020, notice the gap around June and August of 2019

3.2. Model

Since the data rarely changes drastically between data points, the baseline model which only uses the shifting method has a good accuracy on its own already. To make use of this situation, residual networks are implemented to the model to help with faster converging and better performance by building upon the baseline model which has a good performance. Inside the residual wrapper, two consecutive layers of LSTM and a dense layer are built. The first LSTM layer consists of 4,864 parameters, the second LSTM layer consists of 8320 parameters, and the dense layer consists of 165 parameters, for a total of 13,349 trainable parameters.

For comparison purposes, a total of four other models with different combinations of LSTM layers are also built. First, a standard LSTM model with one LSTM layer and one dense layer for a total of 5,029 trainable parameters. Second, a double LSTM model with two consecutive LSTM layers and one dense later for a total of 13,349 trainable parameters. Third, a recurrent LSTM model with one LSTM layer, one dense layer, and a reshape layer for a total of 8,824 trainable parameters. Note that unlike the other models, the recurrent LSTM model accumulates the data from the previous 24 hours before making a prediction on the last hour, instead of making the prediction every hour. Fourth, an autoregressive RNN model with one LSTM cell layer, one RNN layer, and one dense layer for a total of 9,893 trainable parameters. This model would feed the output back into itself at each step and condition the next predictions based on past outputs. An advantage of this model is its ability to produce outputs at varying lengths, but for the purpose of comparison it will be made to produce the same amount of 24 hours output as the other models.

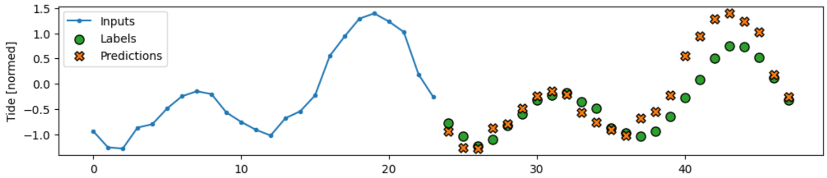
3.3. Training parameters

The model is trained with a dynamic number of epochs and will stop training when no further loss improvement can be made. Due to the simplicity of the data, a maximum number of 50 epochs is set to prevent overfitting the model, although in practice the number of epochs used is only around 20 before no further improvements can be made. MSE is used for loss, to reduce the number of large differences that a normal mean would obscure. The optimizer used is adaptive moment estimation (Adam), which is specifically created for deep learning ANN training. The metrics used for training are mean absolute error (MAE) and RMSE, which is useful for checking whether an extreme deviation is present in the prediction rather than just an average deviation. The MAE would give the absolute deviation of the result, whereas the RMSE would indicate if a single high deviation is present in the result which would be unseen when averaged.

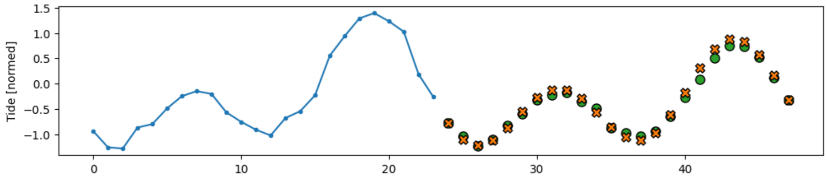
4. RESULTS AND DISCUSSION

The training process for the models are performed in as many as 50 epochs, although in practice the models only used around 20 epochs before no further improvements were made. All models are trained to predict the tidal level for the next 24 hours using the data from the previous 24 hours as reference. The prediction result from each model and the baseline model can be seen in Figure 3.

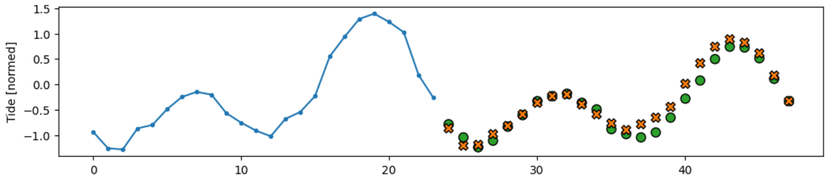
The baseline model seen in Figure 3(a) copied the values from the first 24 hours and pasted in to the second 24 hours. The residual LSTM model seen in Figure 3(b) has the most accurate result compared to the actual values, followed by the double LSTM model seen in Figure 3(c). The single LSTM model seen in Figure 3(d) loosely followed the actual values with some deviation. The recurrent LSTM model seen in Figure 3(e) vaguely followed the previous 24 hours' shape with some adjustments made. Lastly, the autoregressive RNN model seen in Figure 3(f) has the least accurate result compared to the actual values, with the first, smaller high tide completely levelled.



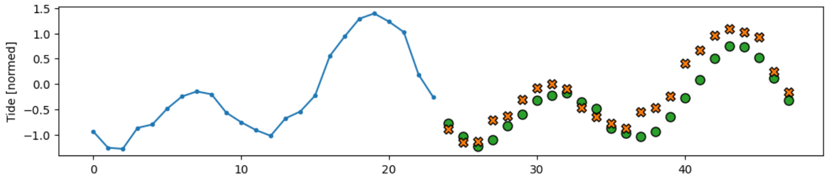
(a)



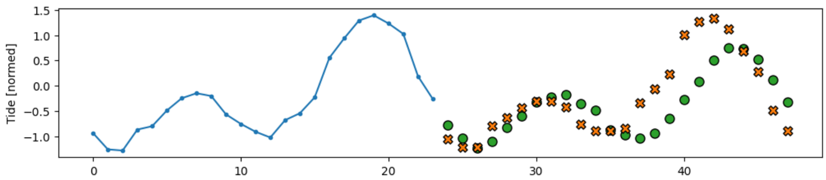
(b)



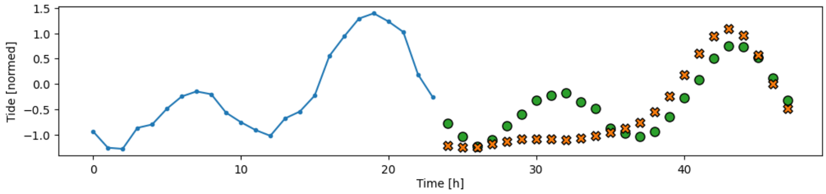
(c)



(d)



(e)



(f)

Figure 3. Tidal level prediction results from the models: (a) baseline, (b) residual LSTM, (c) double LSTM, (d) single LSTM, (e) recurrent LSTM, and (f) autoregressive RNN

The detailed results, including loss value, MAE and RMSE in centimetres, and how much RMSE was improved from the baseline model, can be seen in Table 1, with the baseline model on the first column and then followed by the trained models from best performing to worst performing. The loss value uses MSE, while the metrics used are MAE and RMSE. MAE error is used to see how close the predictions are to its actual value in general, but this value cannot show predictions with a high error rate from its actual value. To mitigate this issue, RMSE is also used as a metric, because a prediction with a high error rate would exponentially increase the RMSE value. If both the MAE and RMSE values are similar, then it can be concluded that the potential for a prediction point with high error value is low, and vice versa.

Table 1. Loss and error between the baseline model and other models

Criteria	Baseline	Residual LSTM	Double LSTM	Single LSTM	Recurrent LSTM	Autoregressive RNN
Loss	1.9902	0.1124	0.1246	0.1355	0.1780	0.3970
MAE (cm)	1.1148	0.1495	0.2116	0.2385	0.3105	0.4922
RMSE (cm)	1.4107	0.3353	0.3530	0.3681	0.4219	0.6301
RMSE improvement (%)		76.23	74.98	73.91	70.09	55.33

From the prediction result, it can be seen that both models with two consecutive LSTM layers perform better than the remaining models with only one LSTM layer. However, this does not mean that more trainable parameters will always result in better performance, as seen from the single LSTM model with the lowest number of trainable parameters having a better performance than both the recurrent LSTM model and the autoregressive RNN model with more trainable parameters. Although it does improve accuracy, the number of LSTM layers used did not provide a significant improvement, which is in line with the result of previous research.

Another thing to note is that the autoregressive RNN model which uses RNN layer and LSTM cell layer perform significantly worse than the other four LSTM based models. This corresponds with the notion that LSTM algorithm is better than others when it comes to time series forecasting. Previous research also shows that and an improved LSTM model, such as a residual LSTM model is better than a standard LSTM model, which is in line with the result in this research.

5. CONCLUSION

This study predicts the tidal level in eastern Bintan Island waters using a residual LSTM model and compares its performance with variations of LSTM and RNN models. The residual LSTM model consists of a residual wrapper, and inside of the wrapper consists of two consecutive LSTM layers and a dense layer. The final performance of the residual LSTM model improves its RMSE by 76.23% from the baseline model, compared to the double LSTM’s 74.98%, single LSTM’s 73.91%, recurrent LSTM’s 70.09%, and autoregressive RNN’s 55.33%. The final MAE and RMSE value of the model are 0.1495 cm and 0.3353 cm respectively, compared to the baseline models’ 1.1148 cm and 1.4107 cm respectively. This study shows that a residual LSTM model can give tidal level short-term predictions with a very high accuracy compared to a standard LSTM model or RNN model.

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