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Implementation of LSTM Method on Tidal Prediction in Semarang Region

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ABSTRACT

Semarang is the capital of the Central Java province, located in the north and directly adjacent to the Java Sea. Having an almost flat land condition with a slope of about 0-2%, Semarang City has the opportunity to experience tidal flooding. The occurrence of tides does not have a fixed period. So, it is necessary to predict the height of the tide and the ebb of the seawater. Thus, this research aims to predict tides in the Semarang area using the LSTM method. The data used is tidal data in Semarang waters from 2020 to 2024. The advantage of the LSTM method is its ability to effectively remember time series data or data with long-term dependence. LSTM can store past information using special cells contained in its structure. This research on tidal prediction using the LSTM method with 70% training data trial batch size 32 and epoch 200 obtained the smallest error value, namely the MAE value of 0.0388 and MAPE of 0.0313 which is the best LSTM result.

I. Introduction

Semarang is a city directly adjacent to the Java Sea located in the northern part of Central Java. As the capital of a large province, Semarang is the center of industry and trade [1]. The coastal areas in Semarang City are affected by the city's rapid economic and development growth. Thus, areas that were originally rice fields and ponds have been transformed into industrial, transportation, and even residential areas [2]. This has an impact on the sloping coastal topography of Semarang City with a slope of around 0-2% affecting most of the area is almost the same height as sea level, even in some places below sea level [3].

Areas with lower elevations than sea level are likely to result in tidal flooding, known as rob flooding. Over the past three decades, Semarang has been affected by tidal flooding [4]. On May 23, 2022, the worst tidal flood occurred in the Tanjung Emas Port Area with a height of 1,5 meters [5]. According to the Semarang City government, tidal flooding has the effect of weakening the city's structure regularly [6]. Tidal flooding on the coast of Semarang City occurs especially during high tide [3].

Tides are the movement of sea level or fluctuations caused by the attraction of the sun and moon to the mass of seawater on Earth [7]. Tides influence activities carried out around these waters, such as shipping activities, loading and unloading ships, and so on [8]. Information on tides can be used as supporting information in planning related to activities in coastal spaces [9].

Previous research discusses the prediction of sea tides with the Backpropagation method, the data used is hourly sea tide data from January 1 to February 11, 2015 totaling 1000 data divided into 700 training data and 300 test data, resulting in an MSE value of 0.0079440 [10]. Then the research discusses the prediction of sea tides with the Support Vector Regression method using tidal data collected from February 4, 2016 to June 10, 2019 as much as 25,246 data, resulting in an RMSE value of 0.4938244 [8].

The research article on air quality in the city of Central Jakarta with the Long Short-Term Memory and Support-

Vector Regression method compares the LSTM and SVR methods in predicting air quality in Central Jakarta. The average MAPE value of LSTM is 12.15% and the average RMSE is 0.0941, while predictions using the SVR method have an average MAPE of 16.19% and an average RMSE of 0.1666. So, the LSTM method is better than SVR [11]. Furthermore, research on the comparison of the Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) methods in rice price forecasting concluded that the LSTM model is more accurate when viewed from the range with actual prices and its RMSE value is smaller than MLP. [12].

The occurrence of tides does not have a fixed period. So it is necessary to predict knowing the tidal height of sea water. Which in the future, can be used as a guide to carry out an activity in these sea waters. [10]. Therefore, this study aims to predict the tides in Semarang with data used per six hours using the LSTM method.

II. METHOD

The initial stage is collecting and the next stage is data preprocessing as an improvement in data processing and preventing errors in the data mining process. In this study, data preprocessing was carried out by filling in empty data and normalizing the dataset in the form of data in the range of zero to one. Next, the data is divided into two parts, namely training data and testing data [13]. The next stage is the implementation of LSTM by determining the parameter values in the form of batch size and number of epochs. Then denormalize the data by inverse or reversing the data as it was originally. Next, evaluate the model using MAE and MAPE evaluation. Followed by visualization of testing models to see the comparison of actual and predicted data visually and numerically.

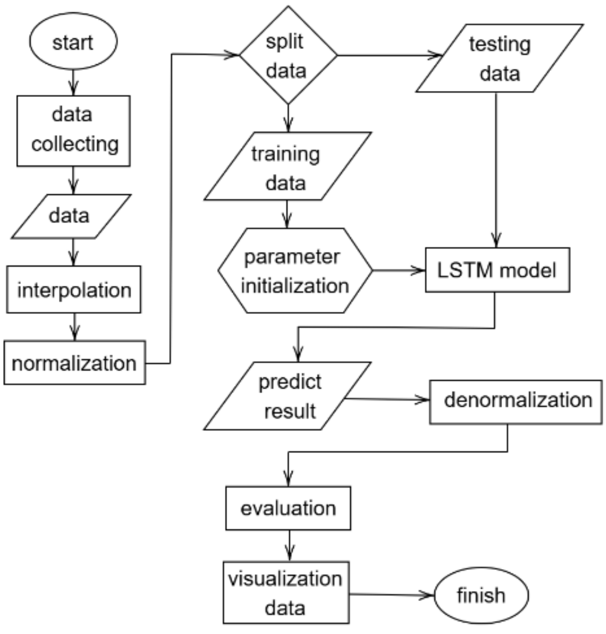

Figure 1. Flowchart

A. Dataset

The data used in this study were obtained from the web [14] in the form of tidal data in Semarang waters from June 1, 2020 to April 30, 2024 with a period per minute. The data collected amounted to 1,694,665 data which were then merged into an excel file.

TABLE I
TIDAL DATA PER ONE MINUTE

No	Time (UTC)	prs(m)
1	2020-06-01 00:00:00	1.282
2	2020-06-01 00:01:00	1.284
3	2020-06-01 00:02:00	1.233
4	2020-06-01 00:03:00	1.276
5	2020-06-01 00:04:00	1.285
…	…	…
1694661	2024-04-30 23:55:00	1.386
1694662	2024-04-30 23:56:00	1.334
1694663	2024-04-30 23:57:00	1.36
1694664	2024-04-30 23:58:00	1.355
1694665	2024-04-30 23:59:00	1.368

B. Prepocessing Data

Prepocessing Data is done to improve data processing and prevent errors in the data mining process. In empty data or undetected values, processing can be done with the interpolation method from the previous and subsequent data on the odd data [15]. Then, normalize the dataset into a range of zero to one using MinMaxScaler, followed by dividing the data into two parts, namely training data and testing data [13].

1) Linear Interpolation

Linear interpolation is a method used to fill in or estimate missing values between two or more known data points. If there are missing values in the data, interpolation can be used to estimate the missing values based on patterns or trends seen in the existing data. [16]. Interpolation calculations can use the formula in equation (1) [17]:

$$\boldsymbol{y = y_1 + \frac{y_2 - y_1}{x_2 - x_1}(x - x_1)} \tag{1}$$

Description:

y = data order that contains empty values
y_1 = data order before empty data
y_2 = data order after empty data
x = interpolated data results
x_1 = order data before empty data
x_2 = order data after empty data

2) Normalization and Denormalization Data

Normalization data is the process of rescaling data into values in the range of zero to one. Normalization is done to overcome data values that have a large range [18]. The normalization process can use the min max method with the formula in the equation (2) [17]:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Description:

x'	=	normalization result
x	=	the value of the data to be normalized
x_{max}	=	maximum value of the data
x_{min}	=	minimum value of the data

Data denormalization is the process of returning the scale of prediction results that are still in the range of zero to one to the previous actual value. Denormalization is done to make it easier to read the prediction results and can be compared with actual data [18]. The denormalization process can use the formula in equation (3) [17]:

$$x = x' \,(x_{max} - x_{min}) + x_{min} \quad (3)$$

C. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a method derived from Recurrent Neural Network (RNN) [19]. The advantages of the LSTM method over the RNN method are that the LSTM is better able to remember time series data or data with long-term dependency information, and the LSTM can store previous information using the cells contained in the LSTM. [20]. The problem of vanishing gradient when processing sequential data can be overcome by the LSTM method with the memory cell [21].

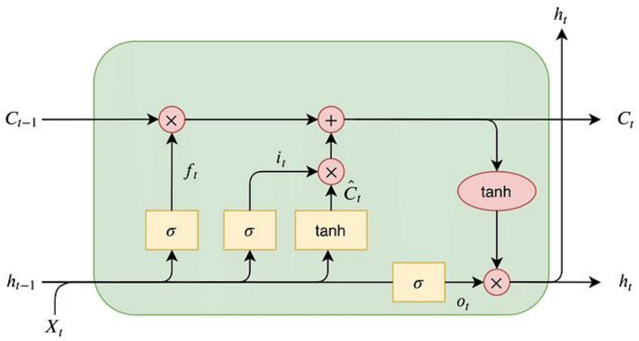

Figure 2. LSTM Architecture

The LSTM architecture consists of three layers, namely the input layer, hidden layer, and output layer [19]. In the hidden layer, there are memory cells and gates units that have a function to organize each memory in the neuron. The stages in the LSTM method process consist of four stages, as follows [22]:

1) Forget gate functions to determine whether the information from each input data is processed and selected which data will be stored or discarded in the memory cell. The forget gate calculation uses the equation (4):

$$\boldsymbol{f_t = \sigma(w_f \times [h_{t-1}, x_t] + b_f)} \quad (4)$$

Description:

$\boldsymbol{f_t}$	=	forget gate
$\boldsymbol{\sigma}$	=	sigmoid activation function
$\boldsymbol{w_f}$	=	bobot matrix forget gate
$\boldsymbol{h_{t-1}}$	=	previous hidden state cell value
$\boldsymbol{x_t}$	=	input value
$\boldsymbol{b_f}$	=	bias forget gate

2) Input gate serves to take the previous output value (h_{t-1}) and the new input (x_t). In the input gate calculation, using a sigmoid activation function to determine which value will be updated and a tanh activation function to create a value vector to be stored in the memory cell. The gate input calculation uses the equation (5) dan (6)

$$\boldsymbol{i_t = \sigma(w_i \times [h_{t-1}, x_i] + b_i)} \quad (5)$$

$$\boldsymbol{\widetilde{C}_t = tanh(w_c \times [h_{t-1}, x_i] + b_c)} \quad (6)$$

Description:

i_t	=	input gate
w_i	=	gate input weight
b_i	=	bias input gate
$\tilde{C}_t$	=	candidate gate
$tanh$	=	tanh activation function

3) Cell state serves to replace the value in the previous memory cell with the latest memory cell value by performing operations on the results of the previous gate unit. The gate input calculation uses the equation (7):

$$\boldsymbol{c_t = i_t \times \widetilde{C}_t + f_t \times c_{t-1}} \quad (7)$$

Description:

c_t	=	cell gate
i_t	=	input gate

4) Output gate functions to determine the value in which part of the memory cell will be output using a sigmoid activation function. The value in the memory cell is placed using the tanh activation function. Finally, the two gates are multiplied to produce the value to be output (h_t). The calculation of the input gate uses the equation (8) dan (9):

$$\boldsymbol{o_t = \sigma(w_o \times [h_{t-1}, x_t] + b_0)} \quad (8)$$

$$\boldsymbol{h_t = o_t \times tanh(c_t)} \quad (9)$$

Description:

o_t	=	output gate
w_o	=	output gate weight
b_o	=	bias output gate
h_t	=	hidden state
c_t	=	cell gate

In the above equation, it shows that the LSTM input not only produces the output h_{t-1} of the hidden layer neuron at the last stage, but also contains the value of the memory unit in the LSTM unit. The LSTM method can avoid gradient loss, so it can remember historical information in the long term on time series data [23].

D. Evaluation Criteria

Evaluation is used to measure the performance of prediction research by calculating the error value of the model. Evaluations that can be used are MAE and MAPE. In the Mean Absolute Error (MAE) error evaluation, the average error value of all data is considered more intuitive [24]. In the context of prediction analysis, a low MAE value indicates better model performance, with predictions closer to the true value [25]. The MAE calculation is obtained from the average value of the absolute error between the results of forecasting and the actual data value. [26].

$$\boldsymbol{MAE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum|\boldsymbol{f_i} - \boldsymbol{y_i}| \quad (10)$$

Description:
f_i = predicted value
y_i = value of i-th observation
n = the amount of data

Furthermore, the Mean Evarage Presentage Error (MAPE) evaluation aims to describe the average error between the actual value and the predicted value [27]. The MAPE calculation can be done by finding the average of the absolute difference between the actual value and the predicted value divided by the actual price [18].

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum\left|\frac{\boldsymbol{y} - \boldsymbol{\hat{y}}}{\boldsymbol{y}}\right| \quad (11)$$

Description:
$\hat{y}$ = predicted value
y = value of i-th observation
n = the amount of data

III. RESULT AND DISCUSSION

The first step is to preprocess the data by summarizing the data based on the average to per six hours in the data in Table I, so that the data collected becomes 5720 data. Next, empty data was checked, and 820 empty data or undetected data were found. On undetected data, it is resolved by interpolating using Equation (1). So, the results obtained are based on Table II.

TABLE II
SIX-HOUR TIDAL DATA

No	Time (UTC)	prs(m)	prs(m) normalized
1	2020-06-01 00:00:00	1.343694	0.590265
2	2020-06-01 06:00:00	1.576164	0.718682
3	2020-06-01 12:00:00	0.991603	0.395769
4	2020-06-01 18:00:00	1.207144	0.514834
5	2020-06-02 00:00:00	1.339906	0.588172
…	…	…	
5716	2024-04-29 18:00:00	1.330087	0.582748
5717	2024-04-30 00:00:00	1.555517	0.707276
5718	2024-04-30 06:00:00	1.761331	0.820968
5719	2024-04-30 12:00:00	1.148261	0.482307
5720	2024-04-30 18:00:00	1.286600	0.558726

In the next stage, normalize the data using MinMaxScaller with Equation (2) into the interval [0,1] to minimize the error. Next, separate the training data as the formation of LSTM and testing data as validation of the LSTM model that has been created. Training data is used as pattern recognition to adjust the input data and the expected output data. In addition, to improve the performance of the model that will be used against the testing data. In this study, 70% training data and 30% testing data were used. For the implementation of LSTM, experiments were conducted with a combination of the parameters used, namely batch size and epoch. The batch size values used in this study are 32, 64, and 128 with epoch values of 50, 100, and 200, respectively. Next, denormalize the data with Equation (3) to restore the actual value of the previous data.

TABLE III
EVALUATION RESULT VALUES

Batch Size	Epoch	MAE	MAPE	Time (seconds)
32	50	0.0658	0.0526	85.68
	100	0.0621	0.0500	228.54
	200	0.0388	0.0313	420.17
64	50	0.0688	0.0559	64.21
	100	0.0654	0.0514	132.86
	200	0.0590	0.0472	252.18
128	50	0.0811	0.0646	75.54
	100	0.0691	0.0550	145.69
	200	0.0636	0.0510	274.41

Based on Table III above, shows the evaluation results of the LSTM method with time steps of 28 data calculated over the past 7 days to predict day 8. The results show that the large or small batch size and epoch values used in this study affect the results of the error value. The comparison between the results of the MAE and MAPE error values at 70% training data share with the batch size and epoch values that have been tested is not too different. It is shown above that the greater the epoch value, the smaller the error value. However, if the batch size value is getting bigger, the error value will also be bigger.

At 70% training data share with batch size 32 and epoch 200, the MAE value of 0.0388 and MAPE of 0.0313 with the smallest error value are the best LSTM results. This reflects that the model has excellent predictive ability with low absolute and relative error rates. However, in the process of running the data, it takes a relatively long time to get the best results, which is about 420.17 seconds. This duration indicates that the computational complexity of the LSTM, especially with a high number of epochs, requires significant processing time. This can be challenging, especially if the model is to be applied to larger datasets or in situations where training time is a constraint. The next step is to visualize the comparison between actual data and predictions on the testing data.

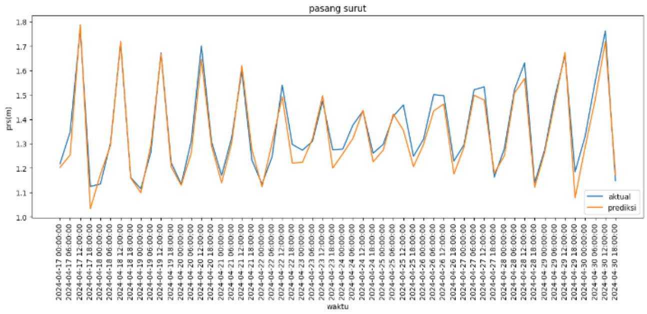

Figure 3. Comparison of Actual Data and Predicted Data

Figure 3 shows a sample graph of the best LSTM model testing data, namely with 32 batch sizes and 200 epochs. The sample data used is 56 final data in the form of data for two weeks. The line graph with yellow color showing the prediction data follows the actual data pattern shown by the blue line. The comparison between actual and predicted data is relatively similar and not too far apart. Furthermore, Table 4 presents a comparison between actual and predicted data in numerical form based on the graph in Figure 3.

TABLE IV
COMPARISON OF ACTUAL DATA AND PREDICTED DATA

No	Actual Data	Predicted Data
1	1.087553	1.063352
2	1.341402	1.328524
3	1.455372	1.485515
4	1.215144	1.245984
5	1.164902	1.122926
...	...	...
1684	1.330087	1.270694
1685	1.555517	1.514290
1686	1.761331	1.766014
1687	1.148261	1.201269
1688	1.286600	1.258151

Based on Table 4, showing the prediction results of the LSTM model against the tidal data, it can be seen that the model managed to capture the tidal pattern quite well, although there are some points where there are differences between the original data and the prediction. In general, the predicted values follow a similar pattern to the original data, indicating that the model is able to predict tidal changes with a high degree of accuracy. However, at some points, especially at the more extreme data, the difference between the actual and predicted values is larger, indicating that the model may have difficulty capturing sudden fluctuations or changes that could be caused by external factors such as weather conditions or other natural events.

These results are particularly relevant in the context of tidal mitigation, as with accurate predictions, coastal communities can be better prepared for potential hazards caused by tidal changes. The model can be used to plan mitigation measures, such as strengthening coastal infrastructure or early notification for tide-affected activities. However, to improve the accuracy of the model, it is important to incorporate external data, such as weather conditions or sea temperature, into the LSTM model. This will help the model better capture the factors that affect tides. In addition, evaluating and retraining the model with a wider range of data can improve its long-term predictive capabilities and provide more effective solutions in the face of more extreme tidal risks.

Research development needs to be done to improve the performance of the model. One direction of development is the optimization of hyperparameters such as the number of units in the LSTM layer, learning rate, dropout rate, and number of hidden layers. In addition, more complex LSTM architectures such as Bidirectional LSTM and Stacked LSTM can be applied to capture more complicated data patterns. Bidirectional Long Short-Term Memory (Bi-LSTM) has two LSTM networks, namely forward and backward, which will be combined at each time sequence so that the model can learn past and future information for each input sequence better [28]. This can be a consideration for further research.

IV. CONCLUSION

Based on the research on tidal prediction using the LSTM method above, with 70% training data sharing with batch size 32 and epoch 200 getting the smallest error value, namely the MAE value of 0.0388 and MAPE of 0.0313 with a processing time of about 420.17 seconds. This explains that tidal prediction using the Long Short-Term Memory method can produce good accuracy, because the smaller the level of error value produced, the more accurate the model makes predictions.

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REFERENCES

[1] F. R. Kusumaningsih, M. J. Umar, F. Hanum, A. Arum, T. R. Fariz, and A. V. Amalia, "Dampak Banjir Pasang Surut (Rob) Terhadap Masyarakat Pesisir Di Kota Semarang," *Semin. Nas. IPA XIII*, pp. 695–702, 2023.

[2] L. A. Karondia, E. Y. Handoko, and H. H. Handayani, "Analisa Kerentanan Pesisir Kota Semarang menggunakan algoritma CVI (Coastal Vulnerability Index)," *Geoid*, vol. 18, no. 1, p. 99, 2022, doi: 10.12962/j24423998.v18i1.12969.

[3] A. A. Egaputra, D. H. Ismunarti, and W. S. Pranowo, "Inventarisasi Kejadian Banjir Rob Kota Semarang Periode 2012 - 2020," *Indones. J. Oceanogr.*, vol. 4, no. 2, pp. 29–40, 2022, doi: 10.14710/ijoce.v4i2.13240.

[4] M. O. Andnur, S. Widada, and A. Dwi, "Analisis Tinggi Muka Air Laut dan Penurunan Muka Tanah untuk Perencanaan Tinggi Lantai Bangunan di Pesisir Utara Kota Semarang Tinggi Muka Air Rata-rata (Mean sea level) Tinggi Muka Air Tertinggi (High Highest Water Level) Tinggi Muka Air Terendah (L," *Indones. J. Oceanogr.*, vol. 04, no. 02, pp. 56–60, 2022.

[5] A. N. Rahman, N. Kurniadin, R. Wumu, and S. I. Suryalfihra, "Identifikasi Luasan Banjir Rob di Kota Semarang Pada Tanggal 24 Mei 2022 Menggunakan Citra Landsat," *J. Geomatics Eng. Technol. Sci.*, vol. 01, no. 02, pp. 50–53, 2023.

[6] D. Setiawan, D. L. Setyowati, H. T. Atmaja, and M. S. Mustofa, "Strategi Bertahan Hidup Masyarakat Terdampak Banjir Rob di Pesisir Semarang," *Pros. Semin. Nas. Pascasarj. Univ. Negeri Semarang*, vol. 6, no. 1, pp. 180–183, 2023.

[7] A. A. Saifullah and A. Hidayat, "Sistem Prediksi Pasang Surut Air Laut Stasiun Meteorologi Maritim Tanjung Emas Semarang Dengan Metode Least Squares," *J. Inform. dan Rekayasa Perangkat Lunak*, vol. 4, no. 2, p. 113, 2022, doi: 10.36499/jinrpl.v4i2.6722.

[8] W. A. Arifin, I. Ariawan, A. A. Rosalia, A. S. Sasongko, and M. R. Apriansyah, "Jurnal Kemaritiman : Indonesian Journal of Maritime Model Prediksi Pasang Surut Air Laut Pada Stasiun Pushidrosal," *J. Kemaritiman Indones. J. Marit.*, vol. 2, no. 2, pp. 105–112, 2021.

[9] V. Wuwung, R. M. Rampengan, H. W. K. Manengkey, R. A. Bara, R. Djamaaludin, and F. Losung, "Acquisition of Tidal Measurement Data in The Waters Around Bitung City For Predictional Purposes," *J. Ilm. PLATAX*, vol. 11, no. 2, pp. 614–622, 2023, doi: 10.35800/jip.v11i2.48800.

[10] N. Nikentari, N. Ritha, and T. Haryadi, "Prediksi Pasang Surut Air Laut Menggunakan Jaringan Syaraf Tiruan Backpropagation," *J. Sustain. J. Has. Penelit. dan Ind. Terap.*, vol. 7, no. 1, pp. 1–6, 2018, doi: 10.31629/sustainable.v7i1.443.

[11] M. E. S. Wicaksono, G. M. Arya Sasmita, and I. P. A. Eka Pratama, "Peramalan Kualitas Udara di Kota Jakarta Pusat dengan Metode Long Short-Term Memory dan Support-Vector Regression," *JITTER J. Ilm. Teknol. dan Komput.*, vol. 4, no. 1, p. 1576, 2023, doi: 10.24843/jtrti.2023.v04.i01.p03.

[12] S. Sen, D. Sugiarto, and A. Rochman, "Komparasi Metode Multilayer Perceptron (MLP) dan Long Short Term Memory (LSTM) dalam Peramalan Harga Beras," vol. XII, no. 1, pp. 35–41, 2020.

[13] S. Hidayatullah and A. Cherid, "Prediksi Temperatur Cuaca di Negara Norwegia Menggunakan Metode LSTM," *Simkom*, vol. 8, no. 2, pp. 187–198, 2023, doi: 10.51717/simkom.v8i2.192.

[14] UNESCO, "map @ www.ioc-sealevelmonitoring.org." https://www.ioc-sealevelmonitoring.org/map.php

[15] T. A. Faisal Muhammad and M. I. Irawan, "Implementasi Long Short-Term Memory (LSTM) untuk Prediksi Intensitas Curah Hujan (Studi Kasus: Kabupaten Malang)," *J. Sains dan Seni ITS*, vol. 12, no. 1, 2023, doi: 10.12962/j23373520.v12i1.106892.

[16] T. Ericko, M. D. Lauro, and T. Handhayani, "Prediksi Harga Pangan di Pasar Tradisional Kota Surabaya dengan Metode LSTM," *J. Ilmu Komput. dan Sist. Inf.*, vol. 11, no. 2, 2023.

[17] M. David, I. Cholissodin, and N. Yudistira, "Prediksi Harga Cabai menggunakan Metode Long-Short Term Memory (Case Study : Kota Malang)," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 7, no. 3, pp. 1214–1219, 2023.

[18] G. Budiprasetyo, M. Hani'ah, and D. Z. Aflah, "Prediksi Harga Saham Syariah Menggunakan Algoritma Long Short-Term Memory (LSTM)," *J. Nas. Teknol. DAN Sist. Inf.*, vol. 08, no. 03, pp. 164–172, 2022.

[19] M. F. Rizkilloh and S. Widiyanesti, "Prediksi Harga Cryptocurrency Menggunakan Algoritma Long Short Term Memory (LSTM)," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 6, no. 1, pp. 25–31, 2022.

[20] T. Lattifia, P. Wira, N. Kadek, and D. Rusjayanthi, "Model Prediksi Cuaca Menggunakan Metode LSTM," *JITTER- J. Ilm. Teknol. dan Komput.*, vol. 3, no. 1, 2022.

[21] Y. Karyadi and H. Santoso, "Prediksi Kualitas Udara Dengan Metoda LSTM, Bidirectional LSTM, dan GRU," *JATISI (Jurnal Tek. Inform. dan Sist. Informasi)*, vol. 9, no. 1, pp. 671–684, 2022, doi: 10.35957/jatisi.v9i1.1588.

[22] N. Selle, N. Yudistira, and C. Dewi, "Perbandingan Prediksi Penggunaan Listrik dengan Menggunakan Metode Long Short Term Memory (LSTM) dan Recurrent Neural Network (RNN)," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 9, no. 1, pp. 155–162, 2022, doi: 10.25126/jtiik.2022915585.

[23] T. A. F. Muhammad and M. I. Irawan, "Implementasi Long Short-Term Memory (LSTM) untuk Prediksi Intensitas Curah Hujan," *J. SAINS DAN SENI ITS*, vol. 12, no. 1, 2023.

[24] N. K. Agusmawati, F. Khoiriyah, and A. Tholib, "Prediksi Harga Emas Menggunakan Metode LSTM Dan GRU," *J. Inform. dan Tek. Elektro Terap.*, vol. 11, no. 3, pp. 620–627, 2023, doi: 10.23960/jitet.v11i3.3250.

[25] K. Kurniawan, B. Ceasaro, and Sucipto, "Perbandingan Fungsi Aktivasi Untuk Meningkatkan Kinerja Model LSTM Dalam Prediksi Ketinggian Air Sungai," *JEPIN (Jurnal Edukasi dan Penelit. Inform.*, vol. 10, no. 1, pp. 134–143, 2024.

[26] S. Sautomo and H. F. Pardede, "Prediksi Belanja Pemerintah Indonesia Menggunakan Long Short-Term," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 5, no. 1, pp. 99–106, 2021.

[27] F. Fahira and C. Prianto, "Prediksi Pola Kedatangan Turis Mancanegara dan Menganalisis Ulasan Tripadvisor dengan LSTM dan LDA," *J. Tekno Insentif*, vol. 17, no. 2, pp. 69–83, 2023, doi: 10.36787/jti.v17i2.1096.

[28] D. I. Puteri, "Implementasi Long Short Term Memory (LSTM) dan Bidirectional Long Short Term Memory (BiLSTM) Dalam Prediksi Harga Saham Syariah," *EULER J. Ilm. Mat. Sains dan Teknol.*, vol. 11, no. 1, pp. 35–43, 2023, doi: https://doi.org/10.34312/euler.v11i1.1979.