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Optimizing Bitcoin Price Predictions Using Long Short-Term Memory Algorithm: A Deep Learning Approach

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Abstract

Currently bitcoin is considered an investment tools, the value of bitcoin itself is unstable so it is difficult to predict which can cause losses for bitcoin traders. Some previous research shows that Long Short-Term Memory (LSTM) which is a deep learning approach as an improvement of RNN has the best performance in predicting stocks and cryptocurrencies compared to Support Vector Machine (SVM), Exponential Moving Average (EMA), and Moving Average (MA), and Seasonal Autoregressive Integrated Moving Average (SARIMA). LSTM has the disadvantage that it is difficult to understand in determining the best parameters and to obtain good results it needs strict hyperparameter adjustment. This study aims to find the best parameters in LSTM by selecting the amount of data, training data composition, batch size, epoch and the amount of prediction time and analyzing prediction performance. In this study, data collection was carried out in real time and was able to provide predictions for the next few days. The test results of the LSTM algorithm have a performance with an average accuracy of 93.69% with the parameters of the amount of bitcoin price data used is 3 years, with a percentage of train data of 85%, using 10 batch sizes, with a number of epochs 125, and the highest average accuracy rate for 7 days of prediction.

Keywords: Bitcoin, Hyperparameter Tuning, LSTM, Prediction, Real Time Data.

Introduction

Blockchain was introduced by a person or group who named himself as Satoshi Nakamoto in 2009 [1]. Along with blockchain, Satoshi Nakamoto launched the first cryptocurrency called Bitcoin [2]. Currently bitcoin is used as a short-term investment tool (trading) in Indonesia. In addition, bitcoin also allows ownership without identity so that the confidentiality of the owner of an account is guaranteed [3]. In Indonesia alone, bitcoin traders reached 12.4 million in February 2022 [4]. Changes in the price of bitcoin cannot be predicted based on the enthusiasts of bitcoin itself. This causes the price of the bitcoin exchange rate to be very unstable, in just minutes the price of bitcoin can change several times. Bitcoin traders must be observant in monitoring every price change so that they can benefit instead of being harmed by mistakes when making predictions based on this unstable bitcoin exchange rate. In November 2021, the price of bitcoin reached 67,528 USD, then on July 15, 2022 the price of bitcoin reached 20,250 USD. The price fell very drastically with a decrease of 47,278 USD or 70% of the highest price in November 2021. To avoid these losses, traders need accurate predictions in order to avoid large losses. The price of bitcoin can be seen on any crypto trading apps such as Investing.com, Binance, Investopedia, Indodax, Tokocrypto, or other crypto trading apps.

One study that has been widely used by experts to build prediction models is deep learning. Deep learning has a variety of algorithms that focus on learning multilevel nonlinear data representations [5]. One of the deep learning algorithms that has been successfully used to predict time series data is the Long Short Term Memory (LSTM) algorithm which is a derivative of the Recurrent Neural Network (RNN) [6]. The study used 4 different algorithms to build stock price prediction modeling including LSTM, Support Vector Machine (SVM), Exponential Moving Average (EMA), and Moving Average (MA). The results showed that LSTM has the highest accuracy compared to other algorithms [7]. Research comparing 3 algorithms namely LSTM, Facebook prophet, and Seasonal Autoregressive Integrated Moving Average (SARIMA) to predict bitcoin prices states that LSTM has the best performance [8].

Based on the research data presented, the use of the LSTM algorithm to build cryptocurrency and stock price prediction models has good performance. However, LSTM has the disadvantage that it is difficult to understand in determining the best parameters. To obtain good results, strict hyperparameter adjustments are needed. Research to

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predict stock prices in the banking sector using LSTM has a high accuracy value based on the Root Mean Square Error (RMSE) value and the data model obtained at various Epoch values [9]. Research to get the best performance is done by finding the best combination of parameters in the LSTM architecture [10]. Some parameters carried out in the test stage are the percentage comparison of the amount of training data and testing data, time series patterns, hidden neurons, and epoch. From these results, we can use the resulting parameters to be used as a reference in this research stage. Research using different parameters and the same architecture results in different performance and time [11-12].

This study aims to find the best combination of parameters, including the amount of data, training data composition, batch size, epoch and the amount of prediction time and analyze the prediction performance of artificial neural network models with LSTM architecture. The accuracy of the model built to see the feasibility of the model as a consideration for investors or traders in making investment decisions. Based on previous research, each uses datasets that are downloaded manually through different dataset provider sources. This research applies programming code that can be used to retrieve datasets in real time. This research applies the number of prediction time parameters that distinguish it from other studies so that it can produce predictions in the future.

Method

Data analysis and prediction can be described as a process consisting of several steps in which raw data is transformed and processed to produce data visualizations and be able to make predictions using mathematical models based on the collected data. Then, data analysis is nothing more than a sequence of steps, each of which plays a key role in the next. The stages of data analysis and prediction are described as a process chain consisting of data preparation, modeling, validation and visualization. The data preparation consists of data extraction, data cleaning, data transformation and data exploration. The sequence of research stages can be seen in **Figure 1**.

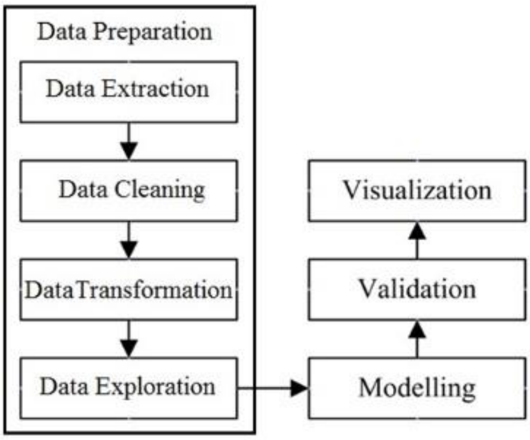

Figure 1. Research stages

1) Data Extraction

In this stage, researchers download data sets available on the internet using a browser and store them in a location that can be accessed by the program [13]. Data that has been downloaded is stored in cloud storage so that it can be accessed through any device as long as it can access the internet. Data is downloaded with program code that can be done in real time when the program is run. The dataset used in this study is bitcoin data on investing.com for 3 years, namely July 16, 2019 to July 15, 2022. Data is downloaded using the InvestPy library which can download data as desired by the user. Determining the date of data download by using the "today()" function as the current date and determining how much data to download based on year multiplication.

2) Data Cleaning

The data cleaning stage is the stage where the author checks and replaces or deletes duplicate data, empty data, or abnormal data that can interfere with the next process [14]. At this stage, the author ensures the columns in the data set to determine which columns are needed. To conduct this research, researchers need date data and bitcoin prices per date, so that, columns other than date and price will be removed to simplify the data set used. Apart from eliminating some columns, data cleaning is also carried out to check and eliminate whether there is abnormal data such as null data or data 0 in the data set used or if there is duplicate data.

3) Data Transformation

Data transformation is the stage of transforming variable data into a form that can be processed by future processing. Some of them are changing the data type to match the criteria needed in modeling [15]. For example, the data type that was previously a string in the Date column needs to be changed to a date data type. In this data transformation process, researchers first check whether the data needs a change in data type or is in accordance with the required data type. The data types needed in this research are float type for price, and datetime type for date.

4) Data Exploration

At this stage, the available data sets are presented and explained and how the data will be processed in the next process. Data that has previously been processed is presented in visual form to make it easier for readers to understand [16]. Data exploration displays data in graphical form to see how the value of the data set. In addition to the graphical form, the data information is displayed again to find out how the data will be used for the modeling process.

5) Modelling

After exploring the data, the information needed for model development can be done. Modeling from LSTM uses a type of regression modeling where the results will be obtained in the form of numbers with the form of time series analysis [17]. LSTM is an algorithm that is known to have the ability to build prediction models. LSTM is a derivative of RNN, a method designed to process sequence data [18]. RNN has vanishing and exploding gradient problems. LSTM was built to overcome the gradient problem in RNN when facing vanishing and exploding gradients [19]. LSTM has the advantage of having a memory block that will determine which value will be selected as the output that is relevant to the input that has been given. The example of LSTM Architecture can be seen in **Figure 2**.

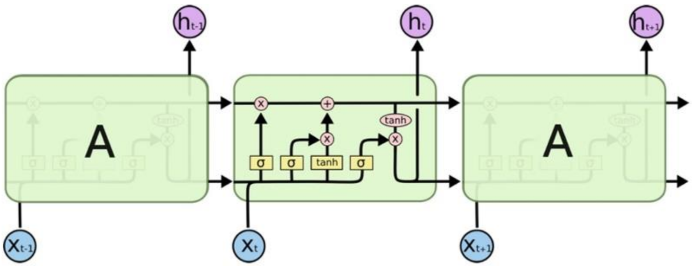

Figure 2. LSTM architecture

The LSTM architecture consists of an input layer, output layer and hidden layer. The hidden layer consists of memory cells, each memory consists of an input gate, forget gate and output gate. The explanation for each gate in LSTM is as follows:

a. Forget Gate (f_t)

Forget gate serves to control the extent to which the value remains in the memory cell. Forget gate is a sigmoid layer that takes the output value at time t-1 and the input value at time t, then combines and applies to the sigmoid activation function. Where the sigmoid output is 0 and 1. If the value of f_t = 1 then the previous state does not change and the data will be stored, while if f_t = 0 then the previous state will be forgotten.

$$f_t \text{ is: } f_t = \sigma\,(W_f S_{t-1} + W_f X_t) \tag{1}$$

b. Input Gate (I_t)

Input gate serves to control the extent to which new values flow in the cell. It aims to avoid unnecessary data storage. The input gate takes the previous output value and the new input value and passes the sigmoid layer. This gate returns the value to 0 or 1.

$$I_t \text{ is: } I_t = \sigma\,(W_i S_{t-1} + W_i X_t) \tag{2}$$

The value of the input gate is then multiplied by the output value of the candidate layer $\hat{C}$.

$$\widehat{C} = \tanh\,(W_c S_{t-1} + W_c X_t) \tag{3}$$

c. Output Gate (O_t)

Output Gate serves to control the number of values that are in the memory cell used to calculate the output value.

$$O_t \text{ is: } O_t = \sigma\,(W_t S_{t-1} + W_t X_t) \tag{4}$$

Before implementation stage of the LSTM method in the program, the data set is first prepared according to the needs of LSTM [20]. The preprocessing stage includes grouping data based on date, determining the amount of training data and test data, reshaping data so that it can be processed in the form of data arrays, and scaling data. Implementation of LSTM by performing a hyperparameter process to evaluate parameters with the best results that will be used in actual predictions. Hyperparameter is done by determining the parameters that will be used in the learning process using the LSTM method [21]. The parameter used in the process can be seen in **Table 1**.

Each type of parameter tested firstly use an initial value. After each test phase, the value used in the next phase is the value that has the highest performance level from each comparison. So it is expected that the performance value continue to improve after each trial stage. The initial value is the value used for the value of each parameter before the parameter is tested. After testing, the parameter with the lowest error result will be used as the default parameter for parameters that are not being tested. The trial value is the value used in testing to get the result with the lowest error rate. The value is taken with the initial value as the center value of each test value for each parameter.

Total Data Set is the amount of data used in the learning process. Train Data is the amount of data used for the training process with a comparison with the data set totaling 100% minus the amount of train data. Batch Size is the number of layers used in each learning process. Epoch is the number of rounds of the learning process every time the entire data set is learned and returns to the beginning. Number of Predictions is the number of days in the future to be predicted.

Table 1. Parameter Test Stages

Testing stage	Parameter	Initial values	Testing values
1	Numbers of datasets (Years)	3	3, 4, 5,6, 7
2	Training data (%)	85	75, 80, 85, 90, 95
3	Batch size	20	10, 15, 20, 25, 30
4	Epoch	100	50, 75, 100, 125, 150
5	Days of predictions	30	7, 15, 30, 45, 60

6) Validation

Validation or testing in this study is measured using Mean Absolute Error (MAE) and Median Absolute Error (MDAE) with the aim of measuring the average error rate and error based on the center line of training data and testing data [22]. The model validation or accuracy measurement stage will determine each parameter that will be used for the next trial stage in accordance with **Table 1**. The accuracy value carried out at this stage determines the number of best values for each parameter.

7) Visualization

The visualization stage is a stage to display the results of the learning process in a form that is easier to understand, namely in the form of a graph [23]. The learning result graph contains comparison data between the actual bitcoin price and the predicted bitcoin price that has been analyzed using LSTM before. This stage is carried out after all trials using hyperparameters have been completed. The results of the trial with the best level of accuracy are displayed in the form of a prediction graph. The prediction graph is displayed using the Plotly library with the Graph Objects class in the python programming code. The graph will display predictions according to the best parameters based on the test results. Both parameters displayed are Close on the vertical axis and Date on the horizontal axis.

Results and Discussion

1) Data Preparation

Real-time data retrieval is done using a library provided by investing.com, InvestPy, installed in python. Data is retrieved by determining the number of years, then using the logic "today's date" minus the number of years or in programming code (date.today() - relativedelta(years=jml_dataset))". Data is taken from investing.com with a time range according to the value of each test parameter of the amount of data in **Table 1**. The downloaded dataset is all bitcoin data starting from Date, Open, High, Low, Close, Volume, and Currency. A comparison of each stage of parameter trial comparison amount of data can be seen in **Table 2**.

Table 2. Parameter Trial Comparison Amount of Data

Years data	Amount of data
3	1096
4	1461
5	1826
6	2191
7	2557

This stage also checks the downloaded data and other info such as the number of rows and columns, non-null count, and data type. There is no data type transformation process because the amount of data currently available is in accordance with the criteria for the type of data needed. In this research, the data used does not have null data or empty data, so it can be continued by eliminating unused data. The data used are the "Date" and "Price" columns. Checking the downloaded dataset, the "Date" column is already of type "datetime64[ns]" or date form and the "Close" column is of type "float64" or float. In this case, data transformation is not needed because the dataset already matches the required criteria. Next, the learning process is carried out using the data that has been prepared. The amount of data used varies on the exploration data shown in **Figure 3**. The price of bitcoin rose began to experience significant price increases and decreases (fluctuations) in January 2021.

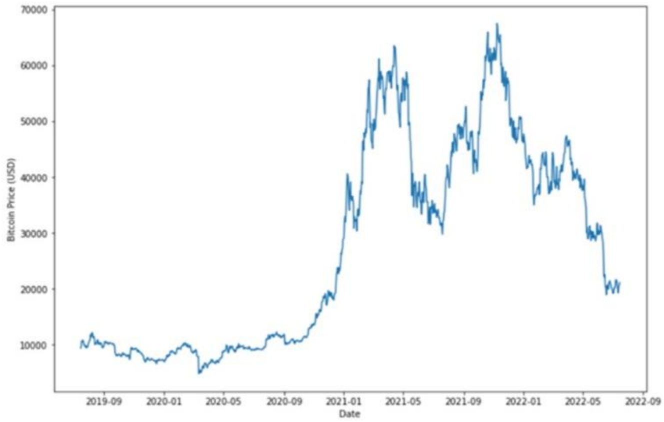

Figure 3. Plot chart of bitcoin price by time

2) Modelling and Evaluation

In this step, the data is prepared to be used in the learning model. The steps in this process are reshaping data, and splitting data to determine training data and testing data. Data reshaping is the process of converting data that was previously in the form of a dataframe into an array. After the data is converted into an array, the next step is to divide the data into training data and testing data. The data division process is carried out based on the parameters in **Table 1.**

The first process is to import classes, namely Sequential, Dense, and LSTM in the Keras library. Learning LSTM uses layer 10, adam as an optimizer, relu as activation, and Mean Squared Error (MSE) to check the error rate during learning so that evaluation can be done. In this process, researchers conducted a trial using the hyperparameters showing in the **Table 1**.

Testing of the learning results using the percentage results of MAE and MDAE. The lower the percentage error, the higher the accuracy. For the first stage of testing, the initial value is used, then continued by changing the parameter value referring to the test value for the number of data sets. And the best accuracy value from the testing stage of the number of data sets is taken to be the value of the number of data sets in subsequent tests. The overall results of the test phase can be seen sequentially in **Table 3** to **Table 7**.

Table 3. Parameterized Number of Data Test Phase

Amount of datasets	Training data	Batch size	Epoch	Numbers of prediction	MAE %	MDAE %
1096	85%	20	100	30	5.86	5.85
1461	85%	20	100	30	8.51	7.03
1826	85%	20	100	30	9.29	8.06
2191	85%	20	100	30	11.02	8.09
2557	85%	20	100	30	13.35	11.34

Table 3 shows that according to the results of stage 1 testing, the amount of data with the highest level of accuracy is in the amount of data 1096 data (3 years). So for the next testing stage using the amount of data for 3 years. Next, proceed to the testing stage with the hyperparameter of the train data value.

Table 4. Parameterized Training Data Test Phase

Amount of datasets	Training data	Batch size	Epoch	Numbers of prediction	MAE %	MDAE %
1096	75%	20	100	30	13.89	12.89
1096	80%	20	100	30	15.17	14.34
1096	85%	20	100	30	11.45	9.22
1096	90%	20	100	30	15.27	15.56

Amount of datasets	Training data	Batch size	Epoch	Numbers of prediction	MAE %	MDAE %
1096	95%	20	100	30	27.02	29.09

In accordance with the test results in Table 4, the amount of train data with the highest accuracy rate is at 85%. So for the next stage of testing using the amount of data train data 85%. Next, proceed to the testing stage with the batch size value hyperparameter.

Table 5. Batch Size Parameter Test Phase

Amount of datasets	Training data	Batch size	Epoch	Numbers of prediction	MAE %	MDAE %
1096	85%	10	100	30	11.57	11.04
1096	85%	15	100	30	14.51	13.15
1096	85%	20	100	30	12.07	11.1
1096	85%	25	100	30	16.82	16.42
1096	85%	30	100	30	16.96	16.76

Table 5 states that according to the results of the previous stage of testing, the number of batch sizes with the highest level of accuracy is at 10. So for the next stage of testing using the number of batch size data 10. Next continued at the testing stage with hyperparameters on the epoch value.

Table 6. Epoch Parameter Test Phase

Amount of datasets	Training data	Batch size	Epoch	Numbers of prediction	MAE %	MDAE %
1096	85%	10	50	30	16.45	16.08
1096	85%	10	75	30	13.6	13.51
1096	85%	10	100	30	16.49	15.91
1096	85%	10	125	30	11.98	10.64
1096	85%	10	150	30	16.47	16.03

In accordance with the results of the test in Table 6, the number of epochs with the highest level of accuracy is at 125. So for the next testing stage using the number of epochs 125. Next continued at the testing stage with hyperparameters on the number of days predicted, seen in Table 7 that the 7th day has the lowest error.

Table 7. Parameterized Number of Predictions Test Phase

Amount of datasets	Training data	Batch size	Epoch	Numbers of prediction	MAE %	MDAE %
1096	85%	10	125	7	6.31	4.28
1096	85%	10	125	15	8.16	6.1
1096	85%	10	125	30	16.93	16.88
1096	85%	10	125	45	11.89	12.56
1096	85%	10	125	60	25.23	27.43

3) Visualization and Interpretation of Results

The results with the highest accuracy are in the hyperparameter by taking the bitcoin price data set for the last 3 years, with the train data used is 85% at batch size 10 with the number of epochs 125, with the number of days predicted is 7 days. Based on these parameters, the MAE percentage is 6.31% and the MDAE percentage is 4.28%. Based on the comparison, it can be seen that the prediction line pattern follows the test data line pattern. Furthermore, the results of the prediction are displayed in graphical form using PyPlot as in Figure 5.

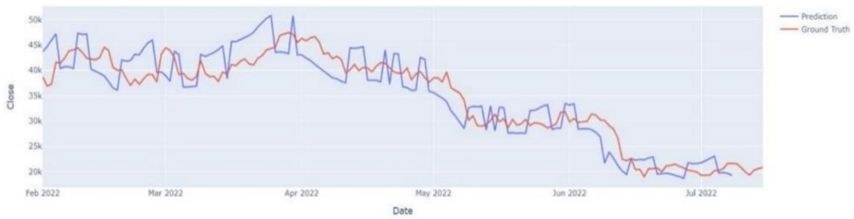

Figure 4. Comparison graph of prediction and test data

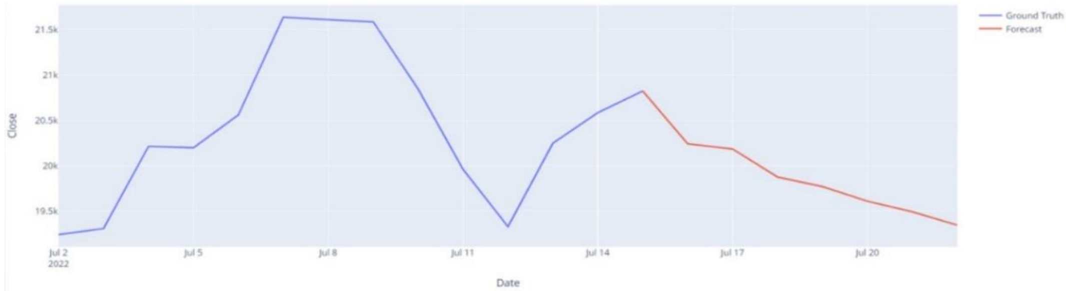

Figure 5. Graphical display of prediction results for the next 7 days

The X-axis of the graph in **Figure 5** displays the date, while the Y-axis displays the price of bitcoin in USD. The blue line on the graph shows the actual price from July 2, 2022 to July 15, 2022. While the red line shows the predicted price of bitcoin from July 16, 2022 to the next 7 days, namely July 22, 2022. Based on **Figure 5**, it can be seen that the price of bitcoin is expected to decrease starting from July 15, 2022 to July 22, 2022. It is recommended that traders do not buy bitcoin on that date range to avoid losses. For Bitcoin prediction values can be seen in **Table 8**.

Table 8. Bitcoin Price Prediction Value for the next 7 days

Date	Predicted value
2022-07-15	20825.100000
2022-07-16	20243.316406
2022-07-17	20185.796875
2022-07-18	19876.980469
2022-07-19	19772.175781
2022-07-20	19611.162109
2022-07-21	19494.740234

Conclusion

Based on the research that has been done, it can be concluded that bitcoin prediction with the LSTM method using the Python programming language has an average accuracy rate of 93.69% and the lowest average error rate of 6.31% after hyperparameter configuration. The optimal hyperparameter configuration is bitcoin price data for 3 years, the number of train data comparisons 85%, batch size 10, number of epochs 125 with the highest accuracy for predicting 7 days. For further development, it can be uploaded to a web or app form that can be accessed online and for optimizing accuracy results, the attributes of transaction volume, initial price, and final price of bitcoin can be added.

References

[1] J.-C. Yen and T. Wang, “Stock price relevance of voluntary disclosures about blockchain technology and cryptocurrencies,” Int. J. Account. Inf. Syst., vol. 40, p. 100499, Mar. 2021, doi: 10.1016/j.accinf.2021.100499.

[2] A. Shoker, “Blockchain technology as a means of sustainable development,” One Earth, vol. 4, no. 6, pp. 795–800, Jun. 2021, doi: 10.1016/j.oneear.2021.05.014.

[3] P. Modesti, S. F. Shahandashti, P. McCorry, and F. Hao, “Formal modelling and security analysis of Bitcoin’s payment protocol,” Comput. Secur., vol. 107, p. 102279, Aug. 2021, doi: 10.1016/j.cose.2021.102279.

[4] I. R. Dewi, “Meledak, Investor Kripto RI Capai 12,4 Juta, Kalahkan Saham,” 2022.

[5] Y. Zhang, W. Zhong, Y. Li, and L. Wen, “A deep learning prediction model of DenseNet-LSTM for concrete gravity dam deformation based on feature selection,” Eng. Struct., vol. 295, p. 116827, Nov. 2023, doi: 10.1016/j.engstruct.2023.116827.

[6] M. J. Islam, R. Datta, and A. Iqbal, “Actual rating calculation of the zoom cloud meetings app using user reviews on google play store with sentiment annotation of BERT and hybridization of RNN and LSTM,” Expert Syst. Appl., vol. 223, p. 119919, Aug. 2023, doi: 10.1016/j.eswa.2023.119919.

[7] T. Gao, Y. Chai, and Y. Liu, "Applying long short term momory neural networks for predicting stock closing price," in 2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS), 2017, pp. 575–578, doi: 10.1109/ICSESS.2017.8342981.

[8] J. Cheng, S. Tiwari, D. Khaled, M. Mahendru, and U. Shahzad, "Forecasting Bitcoin prices using artificial intelligence: Combination of ML, SARIMA, and Facebook Prophet models," Technol. Forecast. Soc. Change, vol. 198, p. 122938, Jan. 2024, doi: 10.1016/j.techfore.2023.122938.

[9] P. A. Riyantoko, T. M. Fahruddin, K. M. Hindrayani, and E. M. Safitri, "Analisis Prediksi Harga Saham Sektor Perbankan Menggunakan Algoritma Long Short Terms Memory (LSTM)," in Seminar Nasional Informatika 2020 (SEMNASIF 2020), 2020, pp. 427–435.

[10] N. Parvini, M. Abdollahi, S. Seifollahi, and D. Ahmadian, "Forecasting Bitcoin returns with long short-term memory networks and wavelet decomposition: A comparison of several market determinants," Appl. Soft Comput., vol. 121, p. 108707, May 2022, doi: 10.1016/j.asoc.2022.108707.

[11] R. K. Rathore et al., "Real-world model for bitcoin price prediction," Inf. Process. Manag., vol. 59, no. 4, p. 102968, Jul. 2022, doi: 10.1016/j.ipm.2022.102968.

[12] S. Rajabi, P. Roozkhosh, and N. M. Farimani, "MLP-based Learnable Window Size for Bitcoin price prediction," Appl. Soft Comput., vol. 129, p. 109584, Nov. 2022, doi: 10.1016/j.asoc.2022.109584.

[13] W. Herwanto, A. Khumaidi, and H. P. Putro, "Feature Extraction and Classification of Tissue Mammograms Based on Grayscale and Gray Level Co-occurrence Matrix," in 2021 International Seminar on Machine Learning, Optimization, and Data Science (ISMODE), 2022, pp. 131–134, doi: 10.1109/ISMODE53584.2022.9743131.

[14] A. Khumaidi, I. A. Nirmala, and H. Herwanto, "Forecasting of Sales Based on Long Short Term Memory Algorithm with Hyperparameter," in 2021 International Seminar on Machine Learning, Optimization, and Data Science (ISMODE), 2022, pp. 201–206, doi: 10.1109/ISMODE53584.2022.9743079.

[15] S. L. Bergquist, T. J. Layton, T. G. McGuire, and S. Rose, "Data transformations to improve the performance of health plan payment methods," J. Health Econ., vol. 66, pp. 195–207, Jul. 2019, doi: 10.1016/j.jhealeco.2019.05.005.

[16] M. Yousefi, E. J. M. Carranza, O. P. Kreuzer, V. Nykänen, J. M. A. Hronsky, and M. J. Mihalasky, "Data analysis methods for prospectivity modelling as applied to mineral exploration targeting: State-of-the-art and outlook," J. Geochemical Explor., vol. 229, p. 106839, Oct. 2021, doi: 10.1016/j.gexplo.2021.106839.

[17] X. Huang et al., "Time series forecasting for hourly photovoltaic power using conditional generative adversarial network and Bi-LSTM," Energy, vol. 246, p. 123403, May 2022, doi: 10.1016/j.energy.2022.123403.

[18] A. Khumaidi, R. Raafi'udin, and I. P. Solihin, "Pengujian Algoritma Long Short Term Memory untuk Prediksi Kualitas Udara dan Suhu Kota Bandung," Telematika, vol. 15, no. 1, pp. 13–18, 2020.

[19] S. Yousuf, S. A. Khan, and S. Khursheed, "Remaining useful life (RUL) regression using Long–Short Term Memory (LSTM) networks," Microelectron. Reliab., vol. 139, p. 114772, Dec. 2022, doi: 10.1016/j.microrel.2022.114772.

[20] E. Koo and G. Kim, "Prediction of Bitcoin price based on manipulating distribution strategy," Appl. Soft Comput., vol. 110, p. 107738, Oct. 2021, doi: 10.1016/j.asoc.2021.107738.

[21] P. Ghosh, A. Neufeld, and J. K. Sahoo, "Forecasting directional movements of stock prices for intraday trading using LSTM and random forests," Financ. Res. Lett., vol. 46, p. 102280, May 2022, doi: 10.1016/j.frl.2021.102280.

[22] Y. He, M. Zhao, T. Xu, S. Li, H. Tian, and W. Li, "Novel cross LSTM for predicting the changes of complementary pelvic angles between standing and sitting," J. Biomed. Inform., vol. 128, p. 104036, Apr. 2022, doi: 10.1016/j.jbi.2022.104036.

[23] S. Mirzaei, J.-L. Kang, and K.-Y. Chu, "A comparative study on long short-term memory and gated recurrent unit neural networks in fault diagnosis for chemical processes using visualization," J. Taiwan Inst. Chem. Eng., vol. 130, p. 104028, Jan. 2022, doi: 10.1016/j.jtice.2021.08.016.