OPEN ACCESS
Indo-JC Indonesia Journal of Computing
ISSN 2460-9056
socj.telkomuniversity.ac.id/indojc

Ind. Journal on Computing
Vol. 6, Issue. 3, December 2021. pp. 17-24
doi:10.34818/indojc.2021.6.3.592

Implementation of LSTM-RNN for Bitcoin Prediction

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Abstract

Bitcoin is a cryptocurrency that is used worldwide for digital payments or simply for investment purposes. Bitcoin is a new technology so there are currently very few prices prediction models available. Problems arise when someone uses bitcoin without understanding strong fundamentals. This can result in a lot of loss for the person. These problems certainly need to be overcome by predicting bitcoin prices using a machine learning approach. The purpose of this research is to predict the bitcoin USD price using the Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) model. The LSTM-RNN model was chosen because it is better than the traditional neural network model. Measurement of the results in this study using the Root Mean Square Error (RMSE) and lost function. The RMSE results obtained on the application of the LSTM-RNN model 0.14, and the lost function is 0.0101.

Keywords: Bitcoin, Prediction, LSTM-RNN, RMSE

Abstrak

Bitcoin adalah mata uang kripto yang digunakan di seluruh dunia untuk pembayaran digital atau hanya untuk tujuan investasi. Bitcoin adalah teknologi baru maka saat ini hanya ada sedikit model prediksi harga tersedia. Permasalahan muncul ketika seorang menggunakan bitcoin tanpa mengerti fundamental yang kuat. Hal tersebut dapat mengakibatkan kerugian yang banyak bagi orang tersebut. Permasalahan tersebut tentunya perlu diatasi denga cara memprediksi harga bitcoin dengan menggunakan pendekatan machine learning. Tujuan pada penelitian ini akan dilakukan prediksi terhadap harga bitcoin USD menggunakan model Long Short-Term Memory Recurrent Neural Network (LSTM-RNN). Model LSTM-RNN dipilih karena lebih baik daripada model jaringan syaraf tiruan yang secara tradisional. Pengukuran hasil pada penelitian ini menggunakan Root Mean Square Error (RMSE) dan lost function. Hasil RMSE yang didapatkan pada penerapan model LSTM-RNN 0.14 dan lost function sebesar 0.0101.

Kata Kunci: Bitcoin, Prediksi, LSTM-RNN, RMSE

I. Introduction

Bitcoin is a cryptocurrency used worldwide for digital payments or for only investment purposes [1]. Currently, there are many people from various circles ranging from young people to middle-class and upper-class entrepreneurs who are starting to look at this crypto currency [2]. However, there are still many who invest in bitcoin without knowing the strong fundamentals so that it will result in huge losses. For this reason, it is necessary to predict the price of bitcoin using a machine learning approach.

Received on October, 2021. Accepted on December, 2021

Currently, there have been many studies related to problems in bitcoin predictions and stock prices. For example, research from Velankar aims tries to predict the price of Bitcoin accurately by considering various parameters that affect the value of Bitcoin [1]. The author aims to understand and identify the daily trends in the Bitcoin market while gaining insight into the optimal features surrounding the Bitcoin price [1]. Jang research about discusses the influence of Bayesian neural networks (BNNs) by analyzing the Bitcoin processing time series [3]. In study Jang, also selects the most relevant features of Blockchain information that are heavily involved in Bitcoin supply and demand and uses them to train models to improve the predictive performance of the latest Bitcoin pricing process [3]. Chen research developed a two-step approach to explore whether information hidden in economic and technological determinants can accurately predict Bitcoin exchange rates [4]. LSTM method produces better predictive values than the Support Vector Regression method, and the adaptive network fuzzy inference system [4]. Gupta research tried to predict the value of bitcoin considering various features that can affect its price. predictions are made using different time series analysis techniques such as moving average, ARIMA, and machine learning algorithms including SVM, linear regression, LSTM, and GRU [5].

Sin research about explores the relationship between Bitcoin features and Bitcoin price changes on the next day using an Artificial Neural Network ensemble approach called Genetic Algorithm based on Selective Neural Network Ensemble, which is built using Multi-Layered Perceptron as the basic model for each neural network in an ensemble, and the best accuracy results using the ensembled method of 53% to 60% [6]. Ji Suhwan research about studied and compared various advanced deep learning methods such as deep neural network (DNN), long short-term memory (LSTM) model, convolutional neural network, deep residual network, and their combination for Bitcoin price prediction [7]. The experimental results show that although the LSTM-based prediction model slightly outperforms the other prediction models for Bitcoin price prediction (regression), the DNN-based model performs best for price fluctuation prediction (classification) [7]. Another research to find the most efficient and highest accuracy model for predicting Bitcoin prices from various machine learning algorithms, using trading data at 1-minute intervals on a Bitcoin exchange site called bit stamp from January 1, 2012, to January 8, 2018, with MSE results obtained by 0.00002 from GRU method [8].

Amjad study aims to introduces a theoretical framework to predict and trade changes in the ternary state of Bitcoin price, i.e. increase, decrease, or no change; and second, using the framework [9]. The author presents a simple, scalable, real-time algorithm that achieves high average returns on Bitcoin investments (e.g., 6-7x, 4-6x, and 3-6x returns on investment for testing in 2014, 2015 and 2016)), while consistently maintaining high predictive accuracy (>60-70%) and a respectable Sharpe Ratio (>2.0) [9]. In addition, when trained on a period eight months earlier than the test period, our algorithm performed almost as well as when trained on the most recent data [9]. The authors justify why it makes sense to use a classification algorithm in settings where the underlying time series is stationary and mixed [9]. Chen study aims to predicts Bitcoin price at different frequencies using machine learning techniques, first, we classify Bitcoin price based on daily price and high-frequency price [10]. A high-dimensional feature set including properties and networks, trading and markets, attention, and spot gold prices are used for daily Bitcoin price predictions, while basic trading features obtained from cryptocurrency exchanges are used for 5-minute interval price predictions. Statistical methods including Logistic Regression and Linear Discriminant Analysis for Bitcoin daily price prediction with high dimensional features achieve 66% accuracy, outperforming more complex machine learning algorithms [10].

Karasu study aims to conducted Bitcoin predictions using Linear Regression (LR) and Support Vector Machine (SVM) from machine learning methods using a time series consisting of daily Bitcoin closing prices between 2012-2018 [11]. Azari research about prediction models with the least included errors are obtained by testing with different combinations of parameters such as SVM by including linear and polynomial kernel functions [12]. Azari study aims to reveal the usefulness of the traditional autoregressive integrative moving average (ARIMA) model in predicting the future value of bitcoin by analyzing the price time series over 3 years [12]. On the one hand, empirical studies reveal that this simple scheme is efficient in sub-periods in which time-series behavior hardly changes, especially when used for short-term predictions, e.g. 1 day [12]. Shu research about applies the log-periodic power law singularity (LPPLS) confidence indicator as a diagnostic tool to identify bubbles using daily data on Bitcoin prices in the last two years [13]. The author found that the LPPLS confidence indicator based on daily Bitcoin price data failed to provide an effective warning to detect bubbles when the Bitcoin price experienced large fluctuations in a short period, especially for positive bubbles [13]. McNally study about determine how accurately the direction of the Bitcoin price in USD can be predicted [14]. Price data is sourced from the Bitcoin Price Index. This task was accomplished with varying degrees of success through the implementation of Bayesian-optimized iterative neural networks (RNNs) and Long Short-Term Memory (LSTM) networks. LSTM achieved the highest classification accuracy of 52% and RMSE of 8%.

Based on the exposure of several previous literature studies. So that in this study a prediction of the bitcoin USD price will be made using the Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) model.

II. LITERATURE REVIEW

A. *Previous Study*

In table 1 is a comparison of the contributions in this study with previous studies.

TABLE I
COMPARISON CONTRABUTIONS

Authors	**Methods**	**Result**
[5]	LSTM	Accuracy 32%
[6]	LSTM, CNN	Accuracy 53% - 60%
[8]	GRU	RMSE 0.00002
[10]	Linear Regression, SVM	Accuracy 66%
This Study	LSTM-RNN	

B. *Long Short-Term Memory Recurrent Neural Network (LSTM-RNN)*

The LSTM contains special units called memory blocks in the iterative hidden layer. The memory block contains self-connected cell memory that stores the temporal state of the working network in addition to special multiplication units called gates to control the flow of information. Each memory block from the original architecture contains input gates and output gates [15]. Moreover, modern LSTM architecture contains peephole connections from internal cells to gates in the same cell to study the exact timing of the output [16].

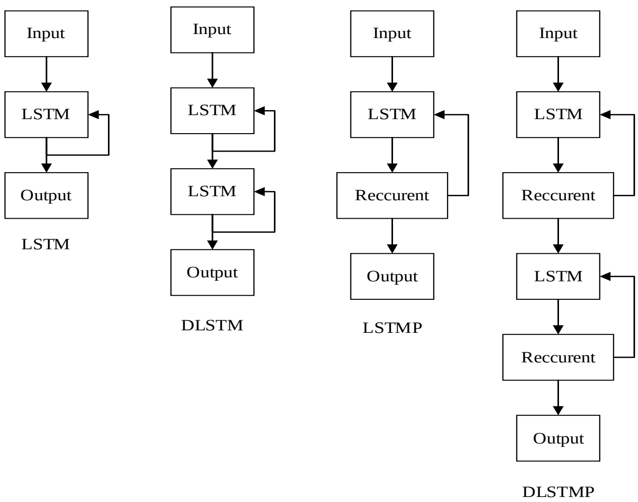

Fig. 1. LSTM-RNN Architecture [15]

Deep learning or deep structured learning can be defined as a special type of neural network consisting of several layers. This network is better than traditional neural networks by retaining information from previous events [17]. Iterative neural network (RNN) is one such machine, which is a combination of networks in circles. loops allow information to persist. Formulas on LSTM (1), (2), (3), (4).

$$cf_t = \sigma 1 \, (W_{cf}.[O_{t-1}, x_t] + b_{cf} \quad (1)$$

$$I_t = \sigma 2 \, (W_t.[O_{t-1}, x_t] + b_t \quad (2)$$

$$S_t = \tanh \, (W_s.[O_{t-1}, x_t] + b_s \quad (3)$$

$$S_t = cf_t \; x \; S_{t1} + I_t \; x \; S_{t-1} \quad (4)$$

Where new information to be stored in the cell state is calculated using two network layers. The sigmoid layer (σ2) decides the value to update (It) (2) and the tanh layer 1 which develops the vector of the new candidate values (St) as shown in (3). Combination of to add in the state. Finally, the cell state is updated using (4).

In the preprocessing step, the data is normalized in the range (0,1) using the normalization function (5).

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (5)$$

This study is to measure the accuracy of the model which calculated the mean squared error using formula (6).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(yii - yi)^2}{n}} \quad (6)$$

Where yii and yi are the predicted and actual values of the workload at the time of sample i respectively and N is the number of sample data.

In addition to using RMSE, this study also calculates the loss value using a loss function (7) [18].

$$Loss\,(p, q) = \frac{1}{|M|} \sum_{i=1}^{i=M} -qiLogpi \quad (7)$$

Where p and q represent predicted labels and true labels, and M denotes batch size.

III. RESEARCH METHOD

In this study, the normalization preprocessing technique and the LSTM-RNN classification model will be used. Figure 2 is a detail proposed system in this research.

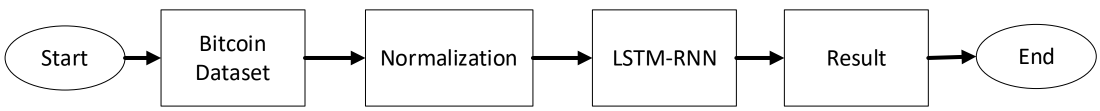

Fig. 2. Proposed Diagram

A. Dataset

The dataset was obtained from the yahoo finance website about bitcoin-USD [19]. The dataset collection period is for one year starting from October 26, 2020, to October 27, 2021. Table II is the characteristics of the dataset used.

TABLE II
CHARACTERISTICS DATASET

No	Features Name	Type
1	Date	Date
2	Open	Float
3	High	Float
4	Low	Float
5	Close	Float
6	Adj Close	Float
7	Volume	Float

Table III is an example of the form of the dataset used.

TABLE III
EXAMPLE DATASET

No	Date	Open	High	Low	Close	Adj Close	Volume
1	Oct 26, 2021	63,032.76	63,229.03	59,991.16	60,363.79	60,363.79	34,878,965,587
2	Oct 25, 2021	60,893.93	63,729.32	60,691.80	63,039.82	63,039.82	31,064,911,614
3	Oct 24, 2021	61,368.34	61,505.80	59,643.34	60,930.84	60,930.84	27,316,183,882
4	Oct 23, 2021	60,694.63	61,743.88	59,826.52	61,393.62	61,393.62	26,882,546,034
5	Oct 22, 2021	62,237.89	63,715.02	60,122.80	60,692.27	60,692.27	38,434,082,775

The date feature is the current date of the transaction on the bitcoin market. The open feature is the opening price of bitcoin on that date. The high feature is the highest bitcoin value that occurred on that day. The low feature is the lowest bitcoin value that occurred on that day. The close feature is the closing price of bitcoin on that date. The adj close attribute is an adjusted closing share price. The volume feature is the number of bitcoins buying and selling transactions that occurred on that date.

B. *Normalization*

At this stage, the dataset is normalized using formula (5). For values that are normalized, the overall value for each feature except for the date feature is not normalized, this is because the date feature is not needed during the LSTM-RNN process the results of the normalization process are as in Table IV.

TABLE IV
NORMALIZATION RESULT

No	Open	High	Low	Close	Adj Close	Volume
1	0	0.01094099	0.00370457	0.00685282	0.00890582	0.01333672
2	0.0125074	0.00898078	0.01653614	0.02000203	0.04733021	0.04706626
3	0.03323103	0.04543516	0.0426525	0.0418699	0.04962607	0.06049209
4	0.06127567	0.05655758	0.05443067	0.06880252	0.08636369	0.0893608
5	0.08960805	0.10480573	0.10520102	0.1000566	0.09994547	0.11399266

C. *LSTM-RNN*

This process is predicted using the LSTM-RNN model using several existing parameters such as epoch, look back, batch size, loss, neuron, and optimizer. Epoch is a parameter that determines the number of times the algorithm will work to process the entire training dataset. The study used an epoch value of 100. Look back is a time step in which one observation point in the sample. In this study, the look back value of 100. Batch size is a parameter to determine the number of samples to be worked on. The study used a batch size of 240. The optimizer in this study uses the "adam" type which is another method to calculate the learning rate for each parameter indicated by the developer to work well in practice and to compare well against other adaptive learning algorithms.

IV. Results And Discussion

The results obtained after applying this research method can be seen in table V. The calculation of the results uses the RMSE formula (6).

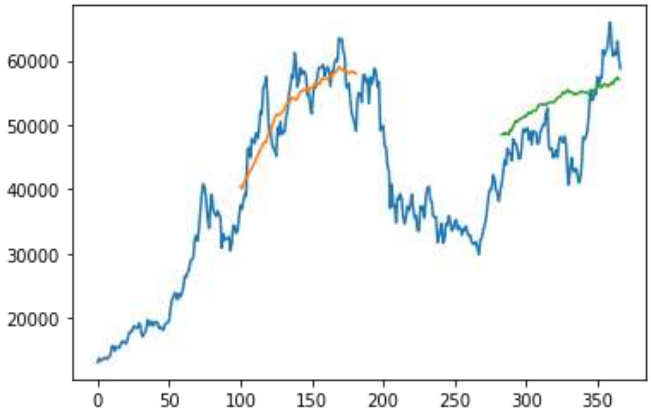

Fig. 3. Graphic Result

Figure 3 is a representation of the results in the form of a graph where some points do not match the original state. In fig 3, the blue line is the actual value of the bitcoin closing price, while the orange and green lines are the predicted bitcoin price. The x-axis in fig 3 is the amount of data in the dataset, the y-axis is the bitcoin value at the closing price. When viewed from the graph of the results above, the actual and predicted values are slightly different. For more details, see Table V is the prediction results obtained using the proposed model of this study.

TABLE V
PREDICTION RESULT

Prediction	Testing	^2
0.72	0.79	0.07
0.73	0.78	0.05
0.73	0.76	0.03
0.73	0.76	0.03
0.72	0.75	0.03
….	….	….
0.83	0.94	0.11

In the testing process, this research uses the close feature on the bitcoin price because this feature is a feature that represents the bitcoin price on that day. It can be seen in table V that the testing value is different from the actual close value, this happens because the feature has gone through the normalization and reshape process using a look back on the LSTM-RNN. In table V for the symbol, ^2 is the RMSE calculation process. After calculating the RMSE process, the overall result of ^2 will be averaged to see the overall RMSE value. So, that the RMSE results in this study are 0.14 and the loss value of this research is 0.0101. The RMSE results indicate that the LSTM-RNN model is suitable for use in bitcoin prediction cases. Because if the RMSE results are smaller than the overall results, the model used is suitable for use in predictions, on the contrary, if the RMSE results are greater than the overall results, the model used is not suitable for this case. The parameters on the LSTM-RNN influence in making predictions. For example, in this study, if the look back parameter is greater than 200, a program error will occur. This happens depending on the amount of data used and the size of the data must match the look back used. In this study, the parameters that have the greatest influence on the prediction results are epoch, lock back, and batch size. So, the limitation in this study is to predict the value of bitcoin based on the parameters of the LSTM-RNN model.

V. CONCLUSION

Based on the results obtained, the conclusion that can be drawn is that the LSTM-RNN model can be used to predict bitcoin prices. The resulting RMSE result is not too high, namely 0.14, so the LSTM-RNN model is good for use in this research case. The loss function value of this study is 0.0101. The parameters of the LSTM-RNN have an influence on the prediction results.

REFERENCES

[1] Velankar, Siddhi, Sakshi Valecha, and Shreya Maji. "Bitcoin price prediction using machine learning." 2018 20th International Conference on Advanced Communication Technology (ICACT). IEEE, 2018.
[2] Mattke, Jens, et al. "Bitcoin investment: a mixed methods study of investment motivations." European Journal of Information Systems 30.3 (2021): 261-285.
[3] Jang, Huisu, and Jaewook Lee. "An empirical study on modeling and prediction of bitcoin prices with bayesian neural networks based on blockchain information." Ieee Access 6 (2017): 5427-5437.
[4] Chen, Wei, et al. "Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants." International Journal of Forecasting 37.1 (2021): 28-43.
[5] Gupta, Aman, and Himanshu Nain. "Bitcoin Price Prediction Using Time Series Analysis and Machine Learning Techniques." Machine Learning for Predictive Analysis. Springer, Singapore, 2021. 551-560.
[6] Sin, Edwin, and Lipo Wang. "Bitcoin price prediction using ensembles of neural networks." 2017 13th International conference on natural computation, fuzzy systems and knowledge discovery (ICNC-FSKD). IEEE, 2017.
[7] Ji, Suhwan, Jongmin Kim, and Hyeonseung Im. "A comparative study of bitcoin price prediction using deep learning." Mathematics 7.10 (2019): 898.
[8] Phaladisailoed, Thearasak, and Thanisa Numnonda. "Machine learning models comparison for bitcoin price prediction." 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE). IEEE, 2018.
[9] Amjad, Muhammad, and Devavrat Shah. "Trading bitcoin and online time series prediction." NIPS 2016 Time Series Workshop. PMLR, 2017.
[10] Chen, Zheshi, Chunhong Li, and Wenjun Sun. "Bitcoin price prediction using machine learning: An approach to sample dimension engineering." Journal of Computational and Applied Mathematics 365 (2020): 112395.
[11] Karasu, Seçkin, et al. "Prediction of Bitcoin prices with machine learning methods using time series data." 2018 26th signal processing and communications applications conference (SIU). IEEE, 2018.
[12] Azari, Amin. "Bitcoin price prediction: An ARIMA approach." arXiv preprint arXiv:1904.05315. 2019.
[13] Shu, Min, and Wei Zhu. "Real-time prediction of Bitcoin bubble crashes." Physica A: Statistical Mechanics and its Applications 548 (2020): 124477.
[14] McNally, Sean, Jason Roche, and Simon Caton. "Predicting the price of bitcoin using machine learning." 2018 26th euromicro international conference on parallel, distributed and network-based processing (PDP). IEEE, 2018.
[15] Sak, Hasim, Andrew W. Senior, and Françoise Beaufays. "Long short-term memory recurrent neural network architectures for large scale acoustic modeling.". 2014.
[16] F. A. Gers, N. N. Schraudolph, and J. Schmidhuber, "Learning precise timing with LSTM recurrent networks," Journal of Ma-chine Learning Research, vol. 3, pp. 115–143, Mar. 2003.
[17] Kumar, Jitendra, Rimsha Goomer, and Ashutosh Kumar Singh. "Long short term memory recurrent neural network (LSTM-RNN) based workload forecasting model for cloud datacenters." Procedia Computer Science 125. 676-682. 2018.
[18] Hu, Yue, et al. "Harmonic loss function for sensor-based human activity recognition based on LSTM recurrent neural networks." IEEE Access 8 (2020): 135617-135627.
[19] https://finance.yahoo.com/quote/BTC-USD?p=BTC-USD. Accessed, 27 October 2021.