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Hybrid gated recurrent unit bidirectional-long short-term memory model to improve cryptocurrency prediction accuracy

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ABSTRACT

Cryptocurrency is a digital currency used in financial systems that utilizes blockchain technology and cryptographic functions to gain transparency and decentralization. Because cryptocurrency prices fluctuate so much, tools for monitoring and forecasting them are required. Long short-term memory (LSTM) is a deep learning model that is capable of strongly predicting data time series. LSTM has been used in previous studies to predict the common currency. In this study, we used the gate recurrent unit (GRU) and bidirectional–LSTM (Bi-LSTM) hybrid model to predict cryptocurrency prices to improve the accuracy and normalize the root mean square error (RMSE) score of previously proposed prediction Using four cryptocurrencies (Bitcoin, Ethereum, Ripple, and Binance), the LSTM model predicts the Bitcoin. The RMSE obtained based on the best experimental results was 2343, Ethereum 10 epoch 203.89, Binance 200 epoch 32.61, and Ripple 200 epoch 0.077, while the mean absolute percentage error (MAPE) obtained for Bitcoin was 4.0%, Ethereum 5.31%, Binance 5.64%, and Ripple 4.83%. The results after normalization RMSE are Bitcoin 0.0062, Ethereum 0.063, Binance 0.073, and Ripple 0.055. The GRU Bi-LSTM hybrid model obtained very good results, yielding small RMSE results. After normalization, the results get closer to 0 and MAPE scores below 10% with RMSE.

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1. INTRODUCTION

Cryptocurrency is a type of virtual or digital currency that is utilized in financial systems that make use of blockchain technology and cryptographic functions to obtain transparency, decentralization, and permanence [1]–[3]. The cryptocurrency market is affected by uncertainty factors such as political issues and economic problems at the global level. Therefore, interpreting predictions accurately is a complicated task. Another problem, which is the focus of this study, is the daily fluctuating prices of cryptocurrencies, which needs to be addressed with an application tool that can monitor and prevent uncertainty in transactions. Automated forecasting techniques are required to assist investors in choosing Bitcoin or other cryptocurrency market assets in order to address the aforementioned fluctuation problem. Now, stock market predictions are often made with the help of automated tools, and strategies for cryptocurrencies are similar.

There are many cryptocurrencies in the cryptocurrency market that are popular today, such as Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and Ripple (XRP). The prices of these cryptocurrencies can be influenced by outside parties, such as news, social media, and cryptocurrency brokers. Hence, to ensure the accuracy of our prediction model, we used these four cryptocurrencies. Previous research has only used neural network algorithms with long short-term memory (LSTM) to forecast the bitcoin. We therefore attempted to improve previous models by using a stacked neural network layer approach consisting of gated recurrent units (GRU) and bidirectional-LSTM (Bi–LSTM) because it processes datasets by looping repeatedly, which increases the predictive ability of the model. In this study, the neural network layer was used because the prediction model used target output in the form of a price prediction from Bitcoin data using historical data and time series over the past 5 years. So, the results can be used as suggestions, and the general public or cryptocurrency traders can use them to make better predictions about the price of Bitcoin.

This study endeavor makes some contributions in the domain of cryptocurrency prediction. Initially, we propose the Hybrid Algorithm GRU and Bi-LSTM models for daily cryptocurrency pricing. To eliminate RMSE anomalies caused by changes in value fluctuations, the researcher normalized the RMSE value, which had not been done in numerous experiments [4]–[7]. The RMSE score is good, and visually the predicted value and the real value are quite close together. Therefore, it is deemed effective in forecasting cryptocurrency. But the RMSE value is high owing to the high and diverse variance from 2,000 to 50,000 dollars. Normalizing and RMSE number might help you understand if it is "good" or not [8]. This attempt was made to balance the MAPE Score, which was fairly excellent. The rest of the paper is organized as follows: section 2 addresses relevant research; section 3 discusses research techniques; section 4 discusses experimental findings and analysis; and section 5 summarizes this study.

2. RELATED RESEARCH

Based on a previous study using LSTM, McNally *et al*. [9] proposed a Bitcoin price method using recurrent neural networks (RNN) and combined RNN with LSTM [10] to propose an automated cryptocurrency price prediction using machine learning techniques based on historical trends (daily trends). Pant *et al*. [11] proposed a prediction of Bitcoin price with looping artificial neural network techniques based on Twitter sentiment, the results of which are quite impressive, showing the relationship between sentiment and LSTM results [12]. Wu *et al.* [12] developed a new framework for predicting the price of bitcoin using LSTM and suggested two different LSTM models: standard LSTM and LSTM with autoregressive integrated moving average (ARIMA) with 208 record datasets, compared to mean absolute error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE). A common stock market prediction model based on LSTM was created by Qian and Chen [13] under various market-influencing conditions. The authors chose three equities with a similar trend. The LSTM prediction model is well done. Hamayel and Owda [5] used three algorithms that each used GRU, LSTM, and Bi–LSTM to get better results and make predictions about cryptocurrencies.

In a previous study [4], a model successfully predicted Bitcoin stock market prices on Yahoo Finance. By sharing the data used to train and test the models outlined above, our model may anticipate prices for the days to come by using time series approaches to generate results. However, in Table 1, the disadvantage is that the results regarding RMSE are not good enough and far from 0.

Table 1. LSTM results

No	Epoch	Model dropout	RMSE results
1	10	0	631.749630
2	100	0	455.981070
3	1000	0	825.375050
4	200	0	360.645110
5	400	0	354.183680
6	500	0	288.598660
7	800	0	292.789670
8	2000	0	477.914280
9	5000	0	474.930575
10	500	0.1	602.140637
11	500	0.5	313.662300

3. METHOD

Cryptocurrency prediction is not much different from the stock prediction method. Better results can be obtained by combining other methods, such as time series data analysis, stock market technical analysis, and historical data from price, with several algorithms [14]–[16]. Furthermore, we can obtain different results by combining several other techniques, such as time series data analysis, market technical analysis that uses historical price data, and combining them with several algorithms to enrich the results. Time-guided data analysis is on historical data presented with 4 periods per day for 5 years.

3.1. Gated recurrent unit

GRU [6] is also a RNN similar to LSTM. However, GRU has a simpler structure than LSTM. GRU does not have an output gate, but it has an update gate zt and a reset gate rt. This gate is a vector that determines whether information should be passed on as an output. Figure 1 describes the GRU unit. The reset gate defines how to combine new input with previous memory. At the update gate, the amount of memory that was last saved is found.

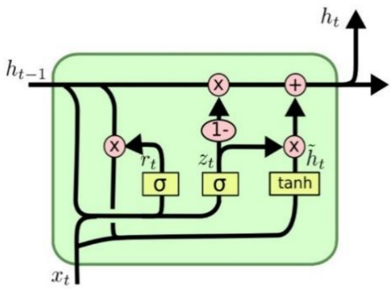

Figure 1. GRU gate

Each element in Figure 2 has the following equations:
– Update gate
$$zt=\sigma(Wzht-1+Uzxt)$$
– Reset gate
$$rt=\sigma(Wrht-1+Urxt)$$
– Cell state
$$h\tilde{}t=tanh(WC(ht-1*r)Ucxt)$$
– New state
$$ht=(z*c)+((1-z)*ht-1)$$
⊗ Element-wise multiplication
⊕ Element-wise summation/concatenation

3.2. LSTM and Bi-LSTM

One more variety of RNN is the LSTM network [7]. With successive data, such as time-series data, LSTM can learn long-term reliance. The input gate i_t, the forget gate f_t, and the output gate o_t are the gates used by LSTM cells. Depending on the importance of the data, this gate determines what can pass. The network can learn what needs to be saved, forgotten, remembered, observed, and created thanks to gates. Data that will be needed for the next state is collected using the cell state and concealed state. Figure 2 depicts the LSTM unit's internal structure.

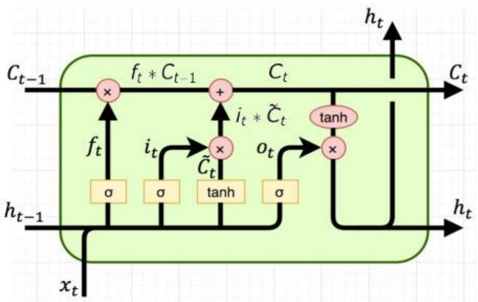

Figure 2. LSTM gates

The gates have the following equations:
- Input gate: $i_t=\sigma(W_i h_{t-1}+W_i h_t)$
- Forget gate: $f_t=\sigma(W_f h_{t-1}+W_f h_t)$
- Output gate: $o_t=\sigma(W_o h_{t-1}+W_o h_t)$
- Intermediate cell state: $\tilde{C}=tanh(W_c h_{t-1}+W_c h_t)$
- Cell state (next memory input): $c_t=(i_t*\tilde{C})+(f_t*c_{t-1})$
- New state: $h_t=o_t*tanh(C_t)$
- X_t : Input vector
- h_t : Output vector
- *W, U, and f:* Parameter matrices and vectors

⊗ Element-wise multiplication

Unlike LSTM, bidirectional LSTM uses two layers, where one layer performs operations in the same direction of time on data while the other layer does the opposite, as shown in Figure 3. BI-LSTM has proven to be more effective than LSTM, which cannot be used in some applications, such as phoneme classification [17].

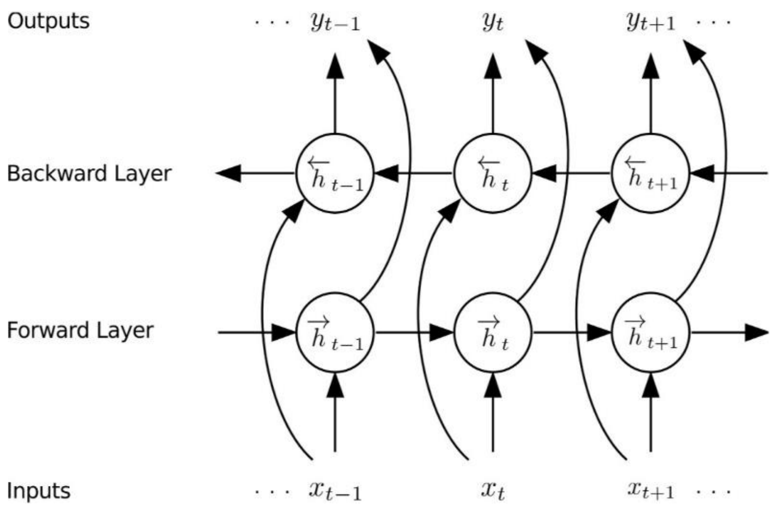

Figure 3. Bi-LSTM workflow

3.3. GRU Bi-LSTM model

A study framework in Figure 4 is a model based on a combination of GRU and Bi-LSTM algorithms that begins by entering a dataset that has been determined by lag windowing with size 2 and batch size 64 based on random tests. These inputs provide better and optimal results for computing. The processed data then passes through two layers of GRU with tanh activation, where the first layer uses 256 units and the second layer uses 128 units. In the Bi-LSTM algorithm, the number of layers used is equal to 2, with the number of units on the first layer being 128 and the number of units on the second layer being 64. However, bidirectional use separates the algorithm into two directions so that the number of parameters generated when data processing is twice as large. The return sequences used at each layer are true [18].

Data that has passed through the GRU and Bi-LSTM layers then passes through the flattening layer, which is used to combine the input data into single data. For example, if the flatten layer is used as input data in the form of (batch_size 2,2), the result of that data will be (batch_size, 4). Then the data is processed through a dense layer. The dense layer is a traditional model of neural networks that performs classification according to the class of the output. The dense layer has an input and an output based on the number of classes predicted. The dense layer in this model uses three layers with different numbers of units: 64, 32, and 1. Lastly, all layer models are arranged using the compiler model with the Adam optimizer. For each cryptocurrency tested, we used historical data over a span of five years. The results obtained for each cryptocurrency will certainly differ. But the MAPE and RMSE values that were found were better than what was found in a previous study that used several other layers.

3.4. Evaluation

3.4.1. Root mean square error

The RMSE will always be greater than or equal to the mean absolute error (MAE). The RMSE matrix assesses how well the model can forecast continuous values. When determining if the error rate is high or low, the RMSE unit is helpful because it is the same unit as the data variable/dependent goal (if it is dollars, then the RMSE is likewise dollars) [19], [20]. Better model performance is associated with a reduced RMSE. In (1) is an explanation of the RMSE formula:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{x}\text{i} - \hat{\boldsymbol{x}}\text{i})\ 2} \quad (1)$$

where N is the total number of observations, $\boldsymbol{x}$i is the actual value, and $\hat{\boldsymbol{x}}$i is the predictive value. The main benefit of using RMSE is that it penalizes big mistakes. It also scales the score in the same unit equal to the approximate value [21].

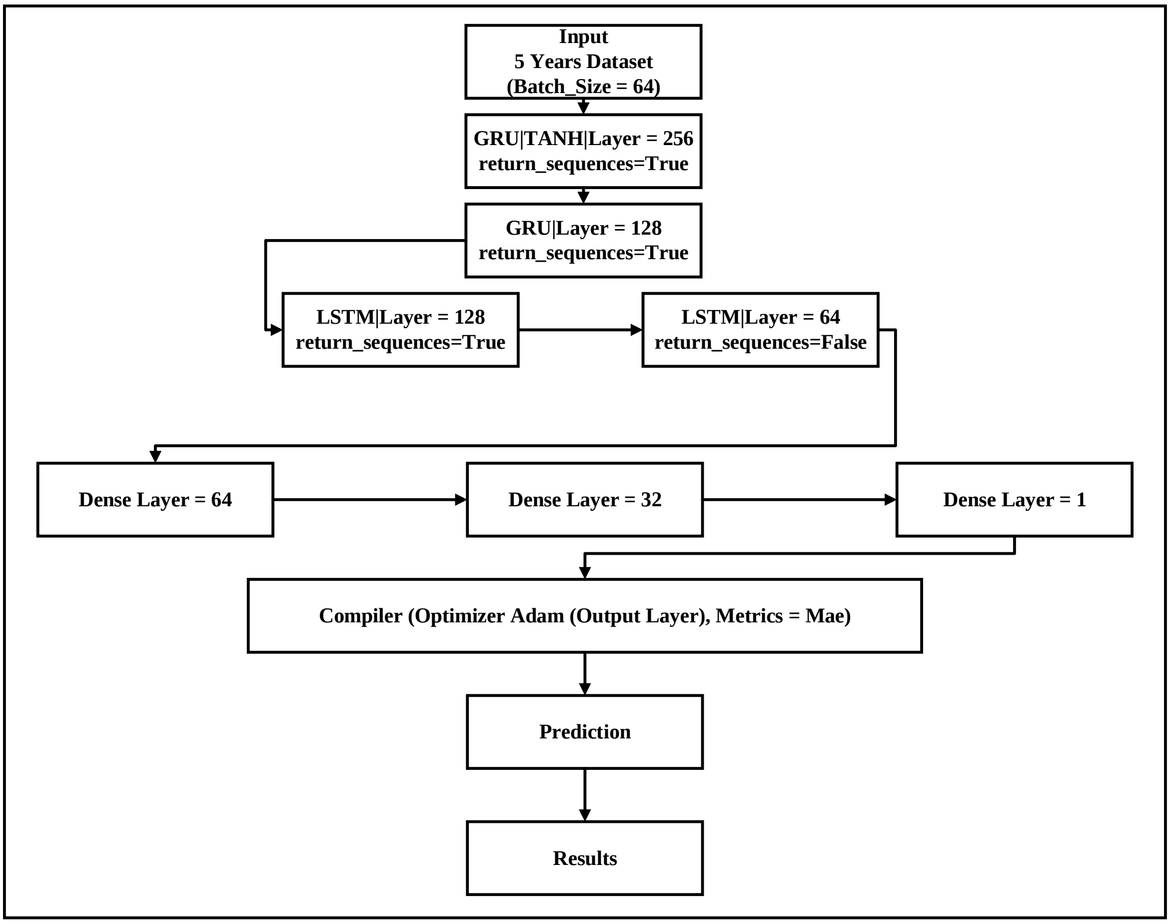

Figure 4. Research framework

3.4.2. Mean absolute percentage error

Similar to mean absolute deviation (MAD) and RMSE, the MAPE is a measure of relative inaccuracy. MAPE is typically more meaningful than MAD because it gives information about error percentages that are either too high or too low when forecasting actual results over a given period. In other words, MAPE is the average of absolute errors over a given period, which is then multiplied by 100% to get the percentage result [22], [23].

$$\text{MAPE} = \sum_{t=1}^{n} \left| \frac{\gamma i - \widehat{y i}}{\widehat{y i}} \right| \times 100\% \quad (2)$$

where:
MAPE = Mean absolute percentage error
n = Total data
y = Actual result value
ŷ = Estimation result value
MAPE value interpretation
Based on Lewis [24], MAPE values can be interpreted into four categories:
<10% =Very accurate
10–20% =Good
20–50% =Fair
>50% =Not accurate

The smaller the MAPE value, the smaller the error in the estimation result; conversely, the larger the MAPE value, the greater the error in the estimated result. The result of the prediction method has excellent forecasting capabilities if the MAPE value<10% and has good predictive capability if the MAPE value is between 10% and 20%.

3.5. Dataset

The datasets for the study were collected from Yahoo Finance's stock market based on the USD exchange rates [25]. Currency in USD, with a 5-year period from August 01, 2017 to January 08, 2022, is the price of the historical data. This study used time-series data in this experiment. The number of rows was 1827 for BTC dataset, for ETH, BNB, and Ripple the total row was 1522 datasets in comma separated value (CSV) format. Figure 5 shows one of the cryptocurrency data used.

Date	Open	High	Low	Close	Adj Close	Volume
2017-01-08	908.174988	942.723999	887.249023	911.198975	911.198975	158715008
2017-01-09	913.244019	913.685974	879.807007	902.828003	902.828003	141876992
2017-01-10	902.440002	914.872986	901.059998	907.679016	907.679016	115808000
2017-01-11	908.114990	919.447998	762.765015	777.757019	777.757019	310928992
2017-01-12	775.177979	826.245972	755.755981	804.833984	804.833984	222326000
...	...	...	...	...	...	...
2022-01-04	46458.851563	47406.546875	45752.464844	45897.574219	45897.574219	42494677905
2022-01-05	45899.359375	46929.046875	42798.222656	43569.003906	43569.003906	36851084859
2022-01-06	43565.511719	43748.718750	42645.539063	43160.929688	43160.929688	30208048289
2022-01-07	43153.570313	43153.570313	41077.445313	41557.902344	41557.902344	84196607520
2022-01-08	41657.835938	42179.816406	41612.550781	41814.644531	41814.644531	50395631616

1827 rows × 6 columns

Figure 5. Bitcoin dataset sample

4. RESULTS AND DISCUSSION

Figure 6 shows the preprocessing process for loading datasets into machines and dividing them into the training, validation, and development datasets. For the data split step, we divided the data into 70% for training, 10% for dataset validation, and 20% for tests. In this study, we used Anaconda and Python for simulation and visualization. We used a Jupyter notebook to display the research results.

We used four cryptocurrencies as a reference to determine whether this GRU Bi-LSTM model provides more accurate predictive results than previous models. RMSE and MAPE were used to determine the accuracy rate of the research with regression data. The magnitude of the RMSE value depends on the value of the dataset used; the greater the RMSE value, the better the accuracy of the model. However, the small value of RMSE also depends on how much value the dataset used [26]. The following formula was used to normalize the RMSE value:

$$\text{Normalized RMSE} = \text{RMSE}/(\text{max value} - \text{min value})$$

The RMSE value obtained by the model was divided by the maximum value of the dataset, which was reduced by its minimum value. Using this method, the RMSE value obtained will have a distance between 1 and 0. Based on Lewis (1982) [24], MAPE scores below 10% are considered very accurate. Table 2 shows comparative results from Hybird GRU-Bi-LSTM Models. According to Table 2, the GRU Bi-LSTM hybrid model yielded small RMSE results and MAPE scores below 10%. The RMSE obtained based on the best experimental results for the Bitcoin dataset within 10 epochs was 2343, Ethereum 10 epoch 203.89, Binance 200 epoch 32.61, and Ripple 200 epoch 0.077, while MAPE obtained based on the Bitcoin dataset was 4.0%, Ethereum 5.31%, Binance 5.64%, and Ripple 4.83%. The values of RMSE and MAPE among cryptocurrencies differed due to differences in the values of each cryptocurrency and the fluctuations within the cryptocurrency that we tested for the prediction value of the model. After using the normalized RMSE formula, the RMSE value of Bitcoin was 0.0062, Ethereum 0.063, Binance 0.073, and Ripple 0.055. There is a difference in the experimental epoch results in the test due to the different value ranges for each cryptocurrency, resulting in different RMSE and MAPE values as well. Based on Figures 7 to 10, we observed differences in the test data and predictions. The difference between the test data and the prediction data was not significantly different, which proves that the GRU Bi-LSTM hybrid model gave good results.

```
# Partition data into data train, val & test
totaldata = dataset.values
totaldatatrain = int(len(totaldata)*0.7)
totaldataval = int(len(totaldata)*0.1)
totaldatatest = int(len(totaldata)*0.2)

# Store data into each partition
training_set = dataset_norm[0:totaldatatrain]
val_set=dataset_norm[totaldatatrain:totaldatatrain+totaldataval]
test_set = dataset_norm[totaldatatrain+totaldataval:]
```

Figure 6. Split data

Table 2. Comparative results

No	Cryptocurrency	Epoch	RMSE	Normalize RMSE	MAPE (%)
1	Bitcoin	10	2343.2200	0.062	4.0
		200	2760.5400	0.073	4.56
		450	3851.0700	0.101	6.53
2	Ethereum	10	203.8900	0.063	5.31
		200	230.7700	0.071	5.86
		450	233.8500	0.072	5.65
3	Binance	10	404.1800	0.916	88.18
		200	32.6100	0.073	5.64
		450	33.2300	0.075	5.69
4	Ripple	10	0.0933	0.066	5.82
		200	0.0770	0.055	4.83
		450	0.0820	0.058	5.37

	Data Test	Prediction Results
0	40254.546875	38580.652344
1	38356.441406	38956.117188
2	35566.656250	37824.695312
3	33922.960938	35664.429688
4	37316.359375	33636.117188
...	...	...
360	45897.574219	44696.679688
361	43569.003906	44054.617188
362	43160.929688	42735.222656
363	41557.902344	41530.117188
364	41814.644531	40605.027344

Figure 7. Actual price and Bitcoin prediction

	Data Test	Prediction Results
0	1772.102417	1845.688110
1	1924.685425	1836.296997
2	1854.564331	1875.045654
3	1791.702271	1928.067017
4	1806.971802	1860.878784
...	...	...
298	3794.056641	3792.995605
299	3550.386963	3771.097168
300	3418.408203	3684.312500
301	3193.210449	3498.992188
302	3210.055420	3331.688965

Figure 8. Actual price and Ethereum prediction

	Data Test	Prediction Results
0	263.685822	278.246429
1	276.104706	275.739838
2	264.636749	263.733978
3	254.660828	267.525085
4	258.100677	256.903595
...	...	...
298	507.506104	507.046295
299	475.056946	494.029327
300	473.275604	480.622131
301	447.788483	460.505829
302	454.637329	450.997803

Figure 9. Actual price and Binance prediction

	Data Test	Prediction Results
0	0.441131	0.442632
1	0.459924	0.430966
2	0.442112	0.444758
3	0.437555	0.432966
4	0.462600	0.426123
...	...	...
298	0.824673	0.824794
299	0.774358	0.813949
300	0.781346	0.770484
301	0.763074	0.768654
302	0.762992	0.754399

Figure 10. Actual price and Ripple prediction

In Figures 11 to 14, the red line is a graph of the test data used, while the blue line is the result of the prediction. The visualization in these graphs was 20% of the total dataset used. Figure 11 shows that the Bitcoin price data chart has a considerable distance. This is because very high price fluctuations cause the model to require more effort to research the data provided. However, the pattern in the data is obvious. Figure 14's chart comparing Ripple prices is the most similar because Ripple prices don't change too much. This shows that the model can learn the data quickly.

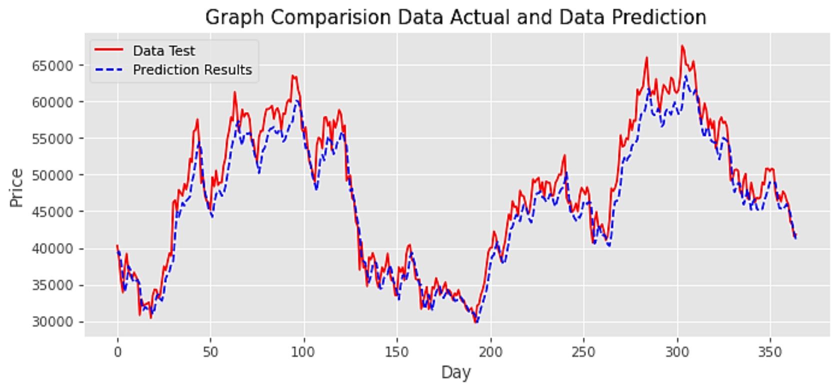

Figure 11. Comparison of actual data and Bitcoin price prediction

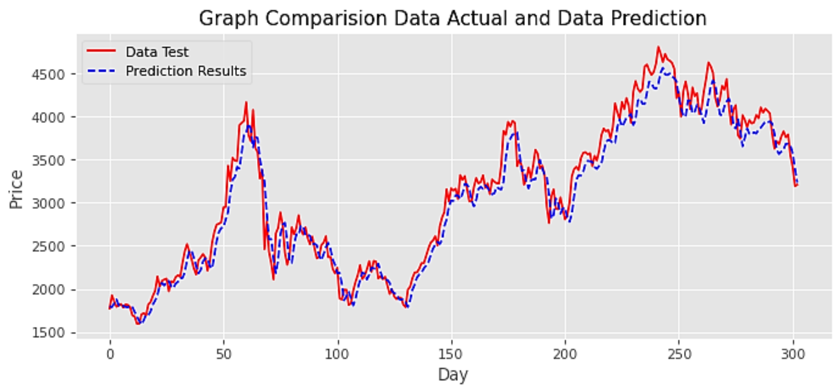

Figure 12. Comparison of actual data and Ethereum price predictions

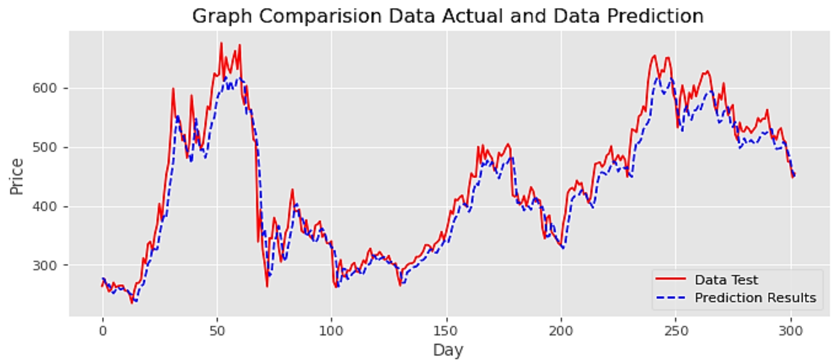

Figure 13. Comparison of actual data and Binance price predictions

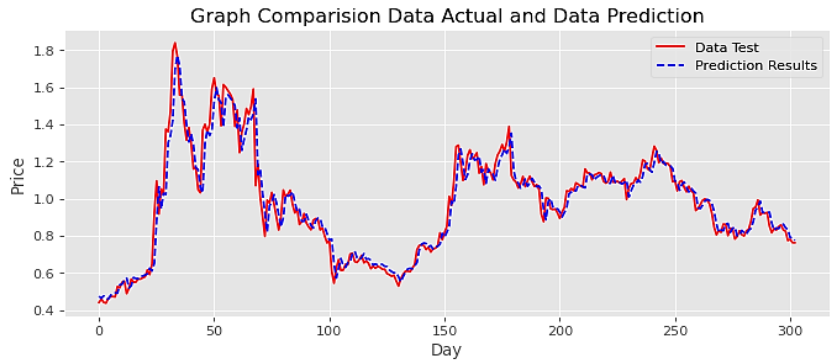

Figure 14. Comparison of actual data and Ripple price predictions

5. CONCLUSION

In this study, we proposed a hybrid model of GRU Bi-LSTM to improve the prediction of cryptocurrency prices. Previous studies have used only one type of deep learning layer, such as GRU or LSTM. The proposed model yielded good results, but the values of RMSE and MAPE still need to be improved. Several approaches were taken in this study to predict the price of cryptocurrency using historical data obtained from the Yahoo Finance website with a timescale of 5 years. Four different cryptocurrencies: Bitcoin, Ripple, Binance, and Ethereum were used to test the accuracy of the suggested model in providing optimal results for each different type of cryptocurrency. Each predicted dataset provided MAPE and RMSE values, which were compared to determine the accuracy of the model. The GRU Bi-LSTM in this study exhibited an excellent level of accuracy. However, the results were not the most accurate, as the RMSE and MAPE values approached 0. Nevertheless, the model improved the accuracy of predicting cryptocurrency prices more than the models offered in previous studies. A future research challenge is to create a model capable of predicting every cryptocurrency with a high level of accuracy. Because cryptocurrencies fluctuate a lot and are all different, it is hard to come up with a prediction model that can give the best RMSE and MAPE values for each coin.

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REFERENCES

[1] U. Mukhopadhyay, A. Skjellum, O. Hambolu, J. Oakley, L. Yu, and R. Brooks, "A brief survey of cryptocurrency systems," *2016 14th Annual Conference on Privacy, Security and Trust, PST 2016*, pp. 745–752, 2016, doi: 10.1109/PST.2016.7906988.

[2] E. Pintelas, I. E. Livieris, S. Stavroyiannis, T. Kotsilieris, and P. Pintelas, "Investigating the problem of cryptocurrency price prediction: a deep learning approach," *IFIP Advances in Information and Communication Technology*, vol. 584 IFIP, pp. 99–110, 2020, doi: 10.1007/978-3-030-49186-4_9.

[3] A. Narayanan, J. Bonneau, E. Felten, A. Miller, and S. Goldfeder, “Bitcoin and cryptocurrency technologies: a comprehensive introduction. [Foreword: The long road to bitcoin],” *Princeton University Press*, p. 304, 2016.

[4] Ferdiansyah, S. H. Othman, R. Zahilah Raja Md Radzi, D. Stiawan, Y. Sazaki, and U. Ependi, “A LSTM-method for bitcoin price prediction: a case study yahoo finance stock market,” in *ICECOS 2019 - 3rd International Conference on Electrical Engineering and Computer Science, Proceeding*, 2019, pp. 206–210, doi: 10.1109/ICECOS47637.2019.8984499.

[5] M. J. Hamayel and A. Y. Owda, “A novel cryptocurrency price prediction model using GRU, LSTM and Bi-LSTM machine learning algorithms,” *Ai*, vol. 2, no. 4, pp. 477–496, 2021, doi: 10.3390/ai2040030.

[6] M. De Caux, F. Bernardini, and J. Viterbo, “Short-term forecasting in Bitcoin time series using LSTM and GRU RNNs,” in *Anais do VIII Symposium on Knowledge Discovery, Mining and Learning*, SBC, 2020, pp. 97–104.

[7] S. Tandon, S. Tripathi, P. Saraswat, and C. Dabas, “Bitcoin price forecasting using LSTM and 10-Fold cross validation,” in *2019 International Conference on Signal Processing and Communication, ICSC 2019*, 2019, pp. 323–328, doi: 10.1109/ICSC45622.2019.8938251.

[8] T. O. Hodson, “Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not,” *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, Jul. 2022, doi: 10.5194/gmd-15-5481-2022.

[9] S. McNally, J. Roche, and S. Caton, “Predicting the price of Bitcoin using machine learning,” in *Proceedings - 26th Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, PDP 2018*, 2018, pp. 339–343, doi: 10.1109/PDP2018.2018.00060.

[10] R. Mittal, S. Arora, and M. P. S. Bhatia, “Automated cryptocurrencies prices prediction using machine learning,” *News.Ge*, vol. 8, no. 4, pp. 1758–1761, 2018, doi: 10.21917/IJSC.2018.0245.

[11] D. R. Pant, P. Neupane, A. Poudel, A. K. Pokhrel, and B. K. Lama, “Recurrent neural network based Bitcoin price prediction by Twitter sentiment analysis,” in *Proceedings on 2018 IEEE 3rd International Conference on Computing, Communication and Security, ICCCS 2018*, 2018, pp. 128–132, doi: 10.1109/CCCS.2018.8586824.

[12] C. H. Wu, C. C. Lu, Y. F. Ma, and R. S. Lu, “A new forecasting framework for bitcoin price with LSTM,” in *IEEE International Conference on Data Mining Workshops, ICDMW*, 2019, vol. 2018-Novem, pp. 168–175, doi: 10.1109/ICDMW.2018.00032.

[13] F. Qian and X. Chen, “Stock prediction based on LSTM under different stability,” in *2019 IEEE 4th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2019*, 2019, pp. 483–486, doi: 10.1109/ICCCBDA.2019.8725709.

[14] M. Jarrah and N. Salim, “A recurrent neural network and a discrete wavelet transform to predict the Saudi stock price trends,” *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 4, pp. 155–162, 2019, doi: 10.14569/ijacsa.2019.0100418.

[15] Z. He, J. Zhou, H. N. Dai, and H. Wang, “Gold price forecast based on LSTM-CNN model,” in *Proceedings - IEEE 17th International Conference on Dependable, Autonomic and Secure Computing, IEEE 17th International Conference on Pervasive Intelligence and Computing, IEEE 5th International Conference on Cloud and Big Data Computing, 4th Cyber Scienc*, 2019, pp. 1046–1053, doi: 10.1109/DASC/PiCom/CBDCom/CyberSciTech.2019.00188.

[16] L. Yu, S. Wang, and K. K. Lai, “A neural-network-based nonlinear metamodeling approach to financial time series forecasting,” *Applied Soft Computing Journal*, vol. 9, no. 2, pp. 563–574, 2009, doi: 10.1016/j.asoc.2008.08.001.

[17] K. A. Althelaya, E. S. M. El-Alfy, and S. Mohammed, “Stock market forecast using multivariate analysis with bidirectional and stacked (LSTM, GRU),” 2018, doi: 10.1109/NCG.2018.8593076.

[18] J. Eapen, D. Bein, and A. Verma, “Novel deep learning model with CNN and bi-directional LSTM for improved stock market index prediction,” in *2019 IEEE 9th Annual Computing and Communication Workshop and Conference, CCWC 2019*, 2019, pp. 264–270, doi: 10.1109/CCWC.2019.8666592.

[19] Zohrahayaty, A. I. S. Azis, and B. Santoso, *Machine learning and reasoning fuzzy logic algoritma, manual, Matlab, and rapid miner*. Indonesia: Deepublish, 2020.

[20] C. Tofallis, “A better measure of relative prediction accuracy for model selection and model estimation,” *Journal of the Operational Research Society*, vol. 66, no. 8, pp. 1352–1362, 2015, doi: 10.1057/jors.2014.103.

[21] N. J. Salkind, *Encyclopedia of research design*. SAGE Publications, Inc., 2012.

[22] D. Chicco, M. J. Warrens, and G. Jurman, “The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation,” *PeerJ Computer Science*, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.623.

[23] U. Khair, H. Fahmi, S. Al Hakim, and R. Rahim, “Forecasting error calculation with mean absolute deviation and mean absolute percentage error,” *Journal of Physics: Conference Series*, vol. 930, no. 1, 2017, doi: 10.1088/1742-6596/930/1/012002.

[24] Colin D. Lewis, “Industrial and business forecasting methods: a practical guide to exponential smoothing and curve fitting,” *Butterworth Scientific*, no. June 1981, pp. 111–153, 1982.

[25] C.- CryptoCompare, “Yahoo! Finance,” *Choice Reviews Online*, vol. 43, no. 12, pp. 43Sup-0514-43Sup – 0514, Aug. 2006, doi: 10.5860/CHOICE.43Sup-0514.

[26] V. B. Kamble and S. N. Deshmukh, “Comparision between accuracy and MSE, RMSE by using proposed method with imputation technique,” *Oriental journal of computer science and technology*, vol. 10, no. 04, pp. 773–779, 2017, doi: 10.13005/ojcst/10.04.11.

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