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RESEARCH ARTICLE

Predicting Bitcoin and Ethereum prices using long short-term memory and gated recurrent unit

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ABSTRACT - Predicting future prices of cryptocurrencies, including Bitcoin and Ethereum, presents a formidable challenge owing to their inherent volatility. This study applies Long Short-Term Memory (LSTM), a well-established recurrent neural network for time series forecasting, to predict Bitcoin and Ethereum values. Historical price data for both cryptocurrencies, sourced from Yahoo Finance, serves as the basis for analysis. The dataset undergoes an 80% training and 20% testing partition. Subsequently, LSTM models are developed and trained on both datasets. In parallel, the gated recurrent unit (GRU), recognized as an advanced variant of the LSTM model, is explored for comparative purposes. Performance evaluation utilizes fundamental metrics, including root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The results reveal an intriguing trend: both models exhibit superior performance when applied to the Ethereum dataset compared to the Bitcoin dataset. This observation suggests the potential presence of Ethereum-specific features or patterns that align more effectively with deep learning model architectures. Notably, the GRU model consistently outperforms the LSTM model across RMSE, MAE, and MAPE. These outcomes underscore the GRU model's capacity as a robust tool for cryptocurrency value prediction. In summary, this study tackles the challenge of cryptocurrency price prediction while emphasizing the promising role of advanced neural network architectures, such as GRU, in enhancing prediction accuracy, thus offering valuable insights into financial forecasting.

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1. INTRODUCTION

Cryptocurrency is a digital currency that people can buy or sell, and all these activities can be done directly without permission from the bank. One example of cryptocurrency is Bitcoin, created by Satoshi Nakamoto in 2009 and shortened to BTC. Bitcoin is an electronic payment system based on cryptography. Since it was launched in 2009, Bitcoin has risen in value. As of today (26th February 2024), the Bitcoin price in Malaysia is RM244,280.02 per one Bitcoin. Any other cryptocurrencies were established after the establishment of Bitcoin. Ethereum is the second largest cryptocurrency after Bitcoin based on market value. Ethereum or Ether (ETH) was launched in 2015 and built on Bitcoin innovation. Vilatik Buterin created Ethereum, and it uses peer-to-peer networks as its blockchain. Ethereum's price is now RM14,624.02, which is equal to one ETH.

Bitcoin and Ethereum work in the same network, but different cryptocurrencies called blockchain. Blockchain is a technology system network known as Distributed Ledger Technology (DLT). Simple terms in a blockchain are a series of data records managed by a group of computers not owned by a single entity. Predicting cryptocurrencies such as Bitcoin and Ethereum is challenging because of their volatility. However, several methods have been tested to predict the future price of Bitcoin and Ethereum. One of the most used methods in predicting cryptocurrencies is Long Short-Term Memory (LSTM). LSTM is a modification of the recurrent neural network (RNN). LSTM is to complete the lack of RNN prediction since it passes information stored over a long period.

LSTM can remember the sets of information that have been stored over the long term, thus removing information that is no longer relevant. It has also proven more efficient at processing, predicting, and classifying databases in specific time orders. Due to all these reasons, many people have chosen this method for predicting cryptocurrency. Among the researchers who researched Bitcoin and Ethereum using LSTM is [1]. Based on the study done by [1], the results showed that bidirectional LSTM (Bi-LSTM) provided more accurate results than traditional LSTM, gated recurrent unit (GRU) and bidirectional GRU (Bi-GRU) when predicting the prices of all digital currencies. Their proposed method, Bi-LSTM, was considered the most effective algorithm for digital currencies.

Other than [1], a group of researchers have studied the prediction analysis of cryptocurrency prices. Their study proposed the LSTM method without hybrid with another method. However, the study focuses on the various factors that

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affect the prediction model, such as market cap, volume, circulating supply, and maximum supply. Their analysis was done using Python, and the results proved that the proposed method accurately predicts cryptocurrency prices based on the various factors included in the model [2]. Finally, a study by [3] compared the price prediction of different cryptocurrencies using technical trade indicators and machine learning. The authors used Python in the analysis of the price prediction. This study predicts the price of a cryptocurrency using a neural network and trading indicators, and the results compare the price before and after the start, which provides a positive prediction for the rest of the month.

Since most of the current studies used LSTM in predicting cryptocurrency, this study applied the same method as well in order to see if it is effective in predicting Bitcoin and Ethereum. Besides LSTM, another method from RNN, GRU was also applied in this study to see if the model developed by this method could outperform the model by using the LSTM method. All methods used in our analysis are presented in the next section. Then, the results are discussed in section III before this study is concluded at the end of this paper.

2. LITERATURE REVIEW

Several studies applied artificial neural network (ANN) and deep learning in cryptocurrency prediction since there are some limitations involving linear models. Some studies combine time series with ANN. For instance, a study by [4] transformed the original Bitcoin time series data, extracting the volatility features of the data before applying ANN for prediction. The proposed method was evaluated using mean average percentage error (MAPE) and root mean squared error (RMSE). It was found that the proposed method outperforms traditional ANN in predicting Bitcoin price.

Another study that applied an ensemble neural network in their study was done by [5]. Bitcoin daily trading volume was predicted using a neural networks-based ensemble machine learning system: radial basis function neural network (RBFNN) and generalized regression neural networks (GRNN). The proposed ensemble methods reduced the prediction errors by 18.81% and 62.86% compared to its components RBFNN and GRNN, respectively. This model was also compared with single feed-forward artificial neural networks (FFNN), and the results showed that the proposed predictive model could reduce prediction error compared to FFNN. The study's results suggested ensemble methods should be used to predict Bitcoin daily trading volume as they are easy to implement and perform quickly.

Besides ANN and its ensemble, deep learning methods such as Long Short-Term Memory (LSTM) and gated recurrent unit (GRU) have been applied in predicting various cryptocurrencies. A study done by [6] applied LSTM, GRU bidirectional LSTM (Bi-LSTM), and bidirectional GRU (Bi-GRU) in predicting the price of Bitcoin. The results from this study show that Bi-GRU outperforms other methods with 0.9986 R-squared value and 295.43 value for mean absolute error (MAE). This study used a dataset from Yahoo Finance, similar to ours. However, the methods proposed in this study only applied the Bitcoin dataset. They have yet to answer whether a similar method, Bi-GRU, works on another cryptocurrency dataset, such as Ethereum.

Although some previous studies prove that ensemble methods like GRNN and Bi-LSTM or Bi-GRU are better in terms of performance, the model involving an ensemble is more complex compared to single or traditional methods. A study by [7] stated that a complex model trained on very little data will surely over-fit that data, especially if there are as many or more parameters than data points. On top of that, this study proved that a complex model is hard to interpret based on the results obtained. This study used Random Forest and gradient-boosting trees, both machine-learning ensemble methods. To interpret the models, the authors had to resort to external inspection tools such as the permutation-based accuracy decrease and the partial dependence plots (PDPs). Although both methods are effective, the importance scores obtained cannot justify whether a variable positively or negatively correlates with the model's prediction.

Thus, in this study, only simple traditional methods were used to predict both datasets obtained from Yahoo Finance. A summary of previous studies that had been conducted using different methods in predicting cryptocurrency is shown in Table 1.

Table 1. Summary of previous studies

Author(s) and Years	Methods Proposed	Results
Gyamerah, 2021 [8]	Two-stage model by combining variational mode decomposition (VMD) with support vector regression (SVR) and technical indicator. This method applied on Bitcoin data only.	The constructed hybrid model outperforms the single SVR model that uses only technical indicators and reconstructed variational mode functions as features.
Ammer and Aldhyani, 2022 [9]	Long Short-Term Memory (LSTM) to forecast the values of four types of cryptocurrencies: AMP, Ethereum, Electro-Optical System, and XRP.	The LSTM algorithm achieved the highest correlation values in training (R^2 = 96.73%) and in testing (R^2 = 96.09%) in predicting XRP currency prices. It also demonstrated superior accuracy based on the low prediction errors of the proposed system.

Table 1. (cont.)

Author(s) and Years	Methods Proposed	Results
Sebastião and Godinho, 2021 [10]	Linear models, Random Forest and suppor vector machine (SVM) were applied to Bitcoin, Ethereum and Litecoin.	The positive results obtained from this study support the claim that machine learning provides robust techniques for exploring the predictability of cryptocurrencies and for devising profitable trading strategies in these markets, even under adverse market conditions.
Alahmari, 2019 [11]	Autoregressive Integrated Moving Average (ARIMA) was applied to Bitcoin, Ethereum and XRP.	ARIMA model on weekly base showed a positive direction for prices in the short term for Bitcoin, XRP and Ethereum. This study also stated a hypothesis that dataset variances did not affect the results as much as the algorithms applied in the study.
Fleischer et al., 2022 [12]	LSTM and ARIMA on cryptocurrency close price.	LSTM outperforms ARIMA in terms of accuracy, minimal RMSE and the predicted value was close to the actual price. However, it took longer time to run LSTM compared to ARIMA.
Dimitriadou and Gregoriou, 2023 [13]	Logistic regression, linear support vector machine and Random Forest (RF) on the Bitcoin,	Results from this study showed logistic regression model outperforms the linear SVM and RF, reaching an accuracy of 66%. This study also provided evidence that points to the rejection of weak form efficiency in the Bitcoin market.

3. METHODOLOGY

This research applied LSTM and GRU to predict Bitcoin and Ethereum. These two methods were proposed based on the literature review that had been done, their performance and the complexity of the models. All the analysis and model development were done in Jupyter Notebook. The flowchart for this study is shown in Figure 1.

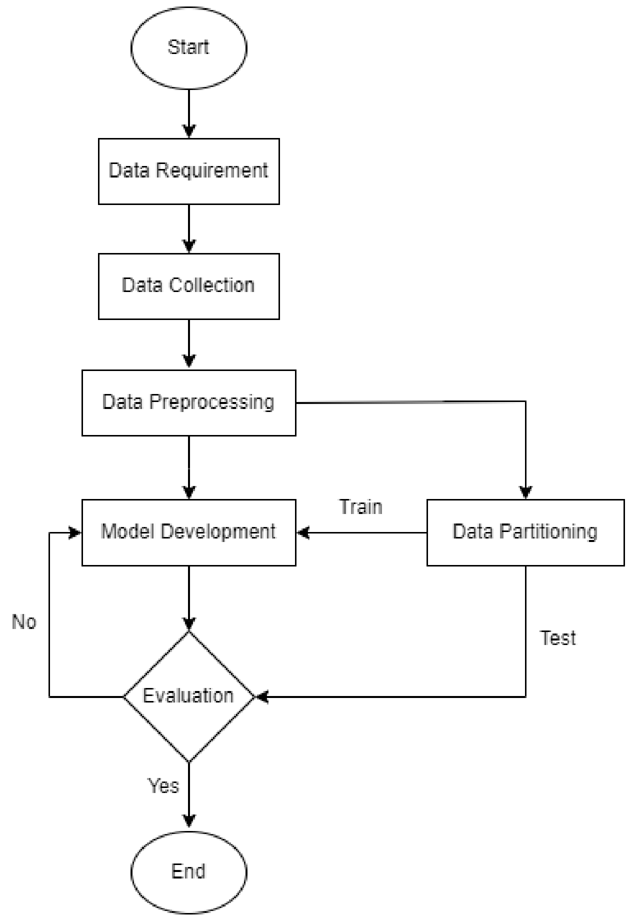

Figure 1. Research framework

3.1 Data Collection

Data in this study were collected from Yahoo Finance from 2018 until 2022. Data retrieved from the website consists of the date, the opening market on that day, the high and low prices on that day, and the market closing price on that day. The price of Bitcoin and Ethereum usually fluctuates from day to day. Hence, the prices are different every day. Bitcoin and Ethereum price movements are determined by supply and demand.

3.2 Data Pre-Processing

This research used the closing prices as time series data for both currencies. Then, data was pre-processed to prepare for analysis using deep learning methods. A missing data was checked, and it was found that both datasets contain no missing values. Data normalization also needs to be done because it helps the deep learning algorithm to converge faster [1]. For normalization, values were scaled using a Min-Max scaler to a range from 0 to 1. The data set has been formed in a way suitable for supervised learning. After scaling, the data is transformed into a prediction of the cryptocurrency price for today based on the previous day.

3.3 Model Development

In the model development phase, this study applied the Long Short-Term Memory (LSTM) model, a common deep-learning recurrent neural network (RNN) in predicting time series data. LSTM has logic gates that allow it to retain more relevant information and forget unnecessary information. This makes LSTM a good model for interpreting patterns over long periods. A gated recurrent unit (GRU) was also applied in this study to see which method performs better by using two different cryptocurrency datasets.

3.3.1 Long Short-Term Memory (LSTM)

The LSTM module has a cell state and three gates that allow it to selectively learn, unlearn, and store information from each unit. The cell state in LSTM helps in the invariance of information flow through the unit by allowing only a few linear interactions. Each unit contains inputs, outputs, and forget gates that can add or remove information from the state of the cell. A forget gate uses a sigmoid function to determine which information from the previous cell state should be ignored. Input gates govern the flow of information to the current cell state by performing multiplication operations on the sigmoid and tanh points. Finally, the output gate determines what data should be transferred to the next concealed state.

3.3.2 Gated Recurrent Unit (GRU)

GRU is quite similar to LSTM. GRU uses gates to control the flow of information. They are relatively new as compared to LSTM. GRUs are designed to process input sequence length and maintain that encodes information about the past. LSTM uses multiple gates and an internal memory cell to control the flow of information. In contrast, GRU uses a single gate to decide which information to retain and a reset gate to decide which information to discard. This makes GRU simple and easier to train compared to LSTM. GRU has the advantage of being able to capture long-term dependencies in sequential data better than ordinary RNNs. This is due to the update and reset gates in a GRU, which allow it to selectively keep or forget knowledge from the past based on the current input and network state. As a result, GRU is particularly well-suited for jobs requiring the capacity to recall and apply information from extended sequences, such as language translation.

3.4 Model Evaluation

Model evaluation is an important step in the model creation process. It also considers how well the selected model will perform in the future. Numerous criteria can be used to evaluate and compare the proposed models. In this study, the models were evaluated using root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE). The best model for each technique is chosen exclusively based on these metrics. Below are the equations for RMSE, MAPE and MAE.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(Yt-yt)^2}{n}} \tag{1}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{yt-Yt}{yt}\right| \tag{2}$$

$$\text{MAE} = \frac{\sum_{t=1}^{n}|Y_t-y_t|}{n} \tag{3}$$

where Y_t is predicted value while y_t is actual value.

4. DATA ANALYSIS, RESULTS AND DISCUSSION

All analysis and results from the LSTM and GRU model development through Jupyter Notebook are presented and discussed in this section. After the model development, all models are evaluated to identify whether the model developed is suitable to be used in predicting the value of Bitcoin and Ethereum.

4.1 Correlation Analysis

To test whether there is a correlation between Bitcoin price and Ethereum price, a scatter graph was plotted, as can be seen in Figure 2. The figure states that the value of the correlation coefficient is 0.9226, implying a strong positive correlation between these two datasets on closing prices. It indicated that the factors under consideration have a significant positive relationship. It is critical to understand that correlation does not indicate the relationship. A high correlation indicates an important connection between the variables, but it does not always mean that one variable causes the other to change.

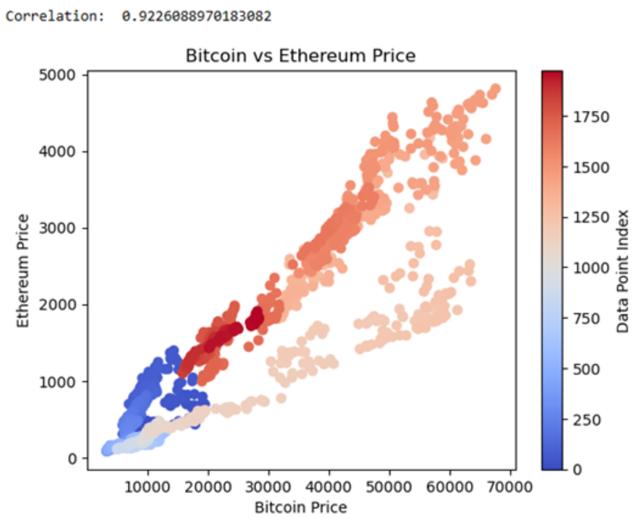

Figure 2. Research framework

4.2 Modelling

Long Short-Term Memory (LSTM) is a deep learning, sequential neural network that allows knowledge to be retained. It is a form of recurrent neural network (RNN) that can handle the vanishing gradient problem that RNN faces. LSTM was created to tackle the difficulty of classical RNN and machine learning methods. The Keras and TensorFlow packages were used to implement LSTM in Python. Before the model development, the close price for Bitcoin, from April 2021 until April 2023, was plotted as shown in Figure 3. The plot shows a decreasing trend until July 2021 and increases from August 2021 until December 2021. A drastic decrease was shown from January 2022 until January 2023. Then, the price started increasing slowly in April 2023.

Figure 1. Research framework

Then, the dataset was divided into two parts: training and testing. The dataset was divided according to the value taken from the close price total data for prediction, which is 730. Based on that, the data was divided into 80% training and 20% testing data. The sequential code was used for modelling, and 100 units of LSTM nodes were added to the model. The 'input_shape' argument sets the shape of the input data, with 'None' indicating a variable-length sequence and '1' indicating that each element in the sequence contains a single feature. The rectified linear unit (ReLU) is the activation function utilized in the LSTM layer. Then, the model was compiled using mean squared error (MSE), often utilized for regression. Adaptive Moment Estimation (ADAM) was chosen for the optimizer as it is a prominent optimization technique.

After the model is developed, the model is trained for the number of epochs specified using the given training data and evaluated on the validation data after each epoch. Figure 4 represents training and validation loss; the blue line represents validation loss, and the red line represents training loss. The epoch in the plot shows a drastic plunge trend for training loss and remains flat. From the plot, it is safe to say that the model is not overfit or underfit. As the trained model produces the desired output, there is no need to change the hyperparameters. The results of the prediction can be used to validate the model. Metrics such as RMSE, MAE, and MAPE were used on the test dataset. Finally, a graph is plotted to show a comparison between the actual value of the close price and the prediction by using LSTM for the Bitcoin dataset. Figure 5 shows the comparison where blue indicates the actual price, red is for the train's predicted price, and green is the test predicted price. The difference between the original and predicted prices is close. Hence, this model is accurate for making a prediction.

Finally, the close price for 30 days was obtained using the developed model. Figure 6 shows that the predicted closing price for the next 30 days will increase. The same process is repeated for model development using the Ethereum dataset. Figure 7 shows the predicted closing price for the next 30 days. From the plot, it can be seen that the close price fluctuates before it increases sharply at the end.

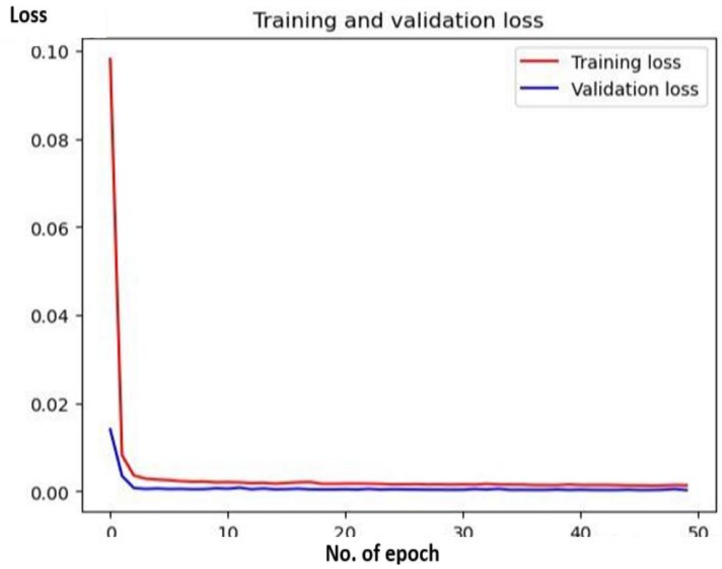

Figure 4. Training and validation loss

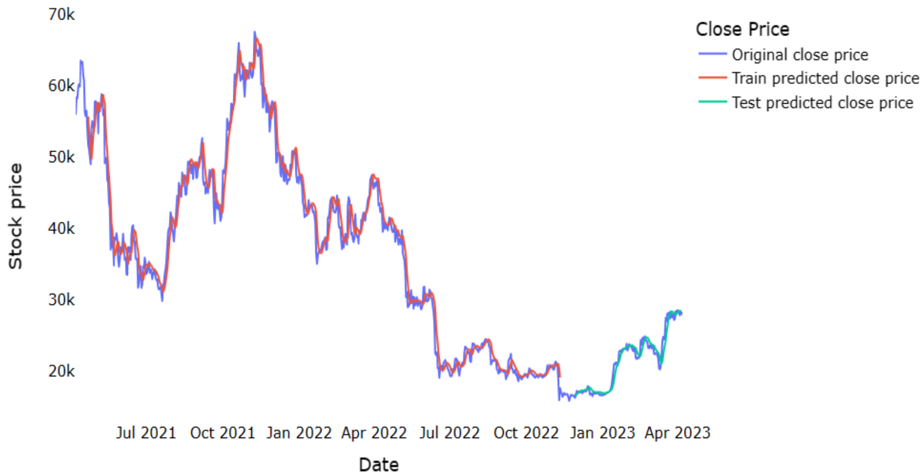

Figure 5. Comparison between actual and predicted close price for Bitcoin

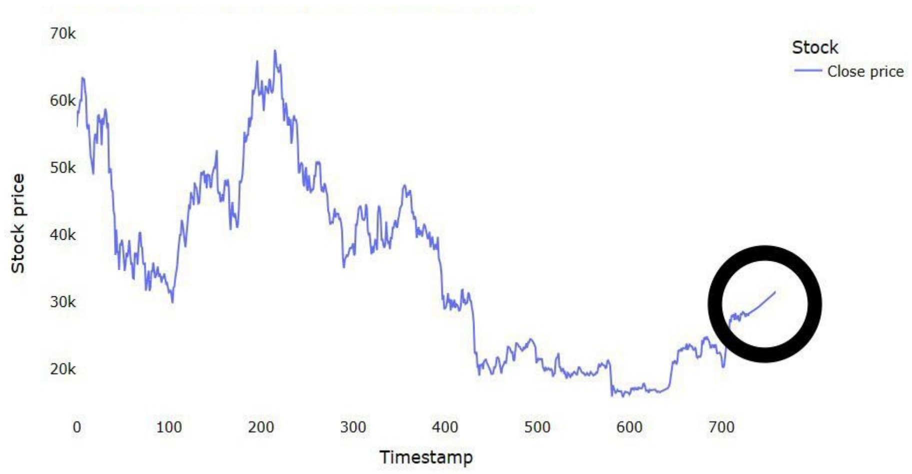

Figure 6. Plotting closing price with a prediction for Bitcoin by using LSTM

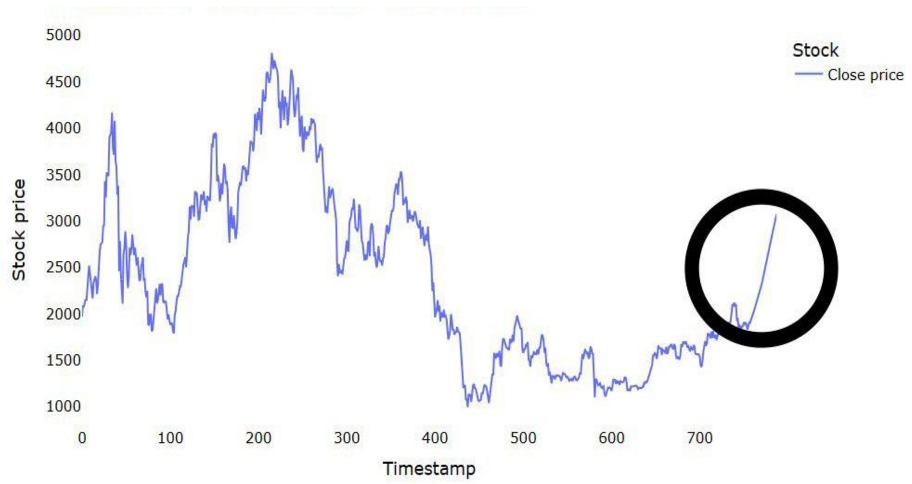

Figure 7. Plotting closing price with a prediction for Ethereum by using LSTM

GRU was employed to see if the model employed in this method is better compared to LSTM. Similar to LSTM, both Bitcoin and Ethereum datasets were used. Python generated all the outputs, and the results obtained will be compared with LSTM. All the parameter settings for GRU are the same as LSTM. Figure 8 and Figure 9 show the plot for the next 30-day prediction. It can be seen from Figure 8 that the predicted close price for Bitcoin will rise and then decrease, which is contradicted by Bitcoin's prediction using the LSTM model. Meanwhile, the predicted close price for Ethereum using GRU will fluctuate and increase slowly, which is slightly different from the prediction by LSTM, as shown in Figure 9.

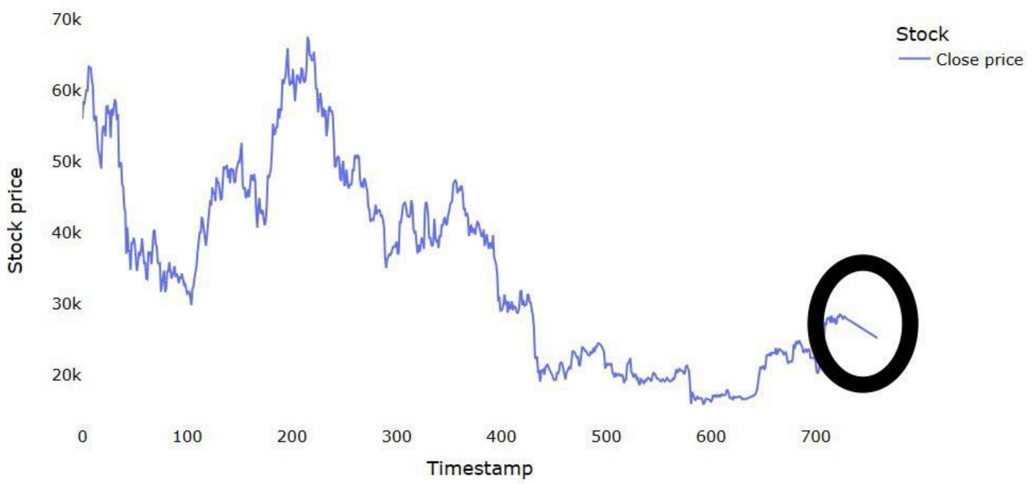

Figure 8. Plotting closing price with a prediction for Bitcoin by using GRU

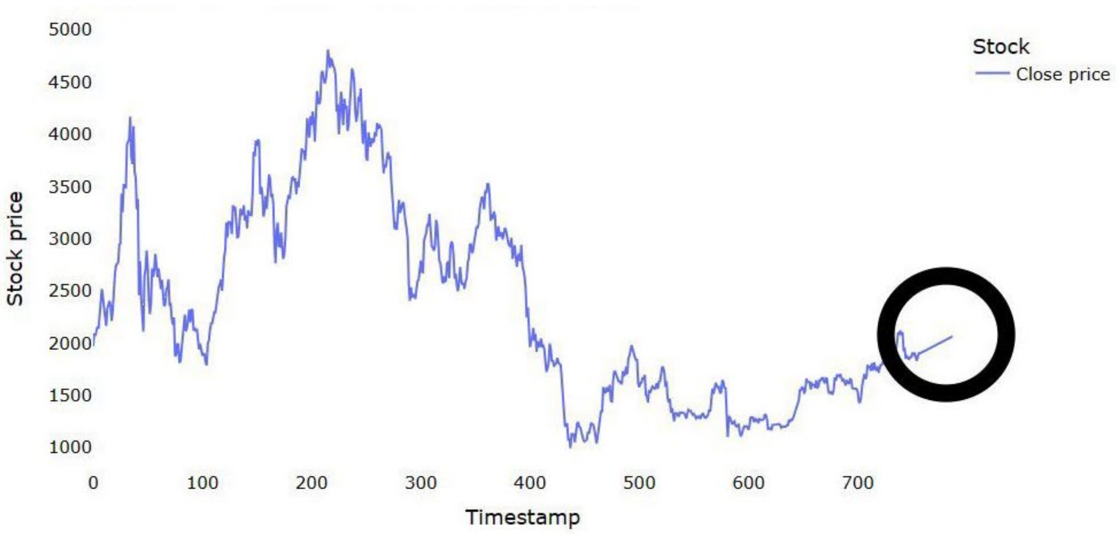

Figure 9. Plotting closing price with a prediction for Ethereum by using GRU

4.3 Comparison of the model performance

Various things must be met while selecting the optimal model, such as choosing a model with low root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean average error (MAE). The lower the MSE, the more accurately the model judges how close predictions are to real value. In the meantime, the study can measure the accuracy using MAPE and MAE by comparing the differences between the real and estimated numbers. Thus, the lower the MAPE and MAE, the better fit of the model.

Table 2 presents a comprehensive comparison of the predictive performance of Long Short-Term Memory (LSTM) and gated recurrent unit (GRU) models using datasets related to Bitcoin (BTC) and Ethereum (ETH). The models are evaluated based on three key metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). These results reveal the predictive capabilities of LSTM and GRU models in forecasting the prices of Bitcoin and Ethereum. Notably, the LSTM model demonstrates higher RMSE and MAE when applied to the BTC dataset than the ETH dataset, indicating that it may be less accurate in predicting BTC prices. Conversely, the GRU model outperforms LSTM when predicting BTC prices regarding RMSE and MAE, suggesting its suitability for BTC price forecasting.

Both models exhibit relatively low MAPE values, indicating their proficiency in providing accurate percentage-based predictions for both cryptocurrencies. These insights contribute to a better understanding of the effectiveness of LSTM and GRU models in the context of cryptocurrency price prediction. From Table 2, GRU fits all the criteria to be selected as the best model. The GRU model has the lowest RMSE, MAPE, and MAE. In all the following evaluations, it is proven that the GRU prediction model outperforms the LSTM prediction model in every aspect.

Table 2. Comparison of all models in terms of RMSE, MAPE and MAE

Metrics	LSTM using BTC dataset	LSTM using ETH dataset	GRU using BTC dataset	GRU using ETH dataset
RMSE	858.9814	64.9446	654.0614	47.3271
MAPE	0.1641	0.1792	0.1382	0.1428
MAE	597.4370	51.6315	422.8203	33.6704

5. CONCLUSIONS

In summary, this study aimed to apply deep learning methodologies to predict cryptocurrency prices, specifically focusing on Bitcoin and Ethereum, utilizing historical data sourced from Yahoo Finance. The research encompassed crucial phases, including data collection, model development, training, and rigorous evaluation, all conducted within the Jupyter Notebook platform. Effective data preprocessing procedures, including removing duplicates and index resetting, were indispensable in ensuring data accuracy and the reliability of our predictive models. The study employed two recurrent neural network architectures, Long Short-Term Memory (LSTM) and gated recurrent unit (GRU), to forecast Bitcoin and Ethereum's closing prices over a 30-day horizon. The performance evaluation involved essential metrics: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). The study's results, consistent with the second objective of model performance comparison, provided valuable insights. The GRU model exhibited superior performance, demonstrating the lowest RMSE, MAPE, and MAE. Additionally, our analysis revealed that both models performed better when applied to Ethereum data than Bitcoin data. This observation hints at distinctive features or patterns in the Ethereum dataset that align more effectively with deep learning models.

Drawing from the methodology and findings of this study, several recommendations can be made to enhance future research in cryptocurrency price prediction:

1) Continuous Monitoring and Retraining: Maintaining a vigilant approach to model performance by regular monitoring and periodic retraining with fresh data can ensure adaptability to evolving market conditions and enhance predictive accuracy over time.
2) Hyperparameter Tuning: For the LSTM model, exploring hyperparameter tuning techniques, including adjustments to learning rates, batch sizes, or epoch counts, may prove beneficial in optimizing performance.
3) Feature Selection: Delving into feature selection methodologies can aid in improving the model's capacity to anticipate Bitcoin value fluctuations by identifying key features with significant impacts on cryptocurrency values.

In conclusion, this study sheds light on the effectiveness of deep learning techniques, particularly the GRU model, in predicting cryptocurrency values. Pursuing the recommended research avenues can further refine predictive capabilities and contribute to advancing cryptocurrency price forecasting methodologies.

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Individual Assistant

NA

AUTHOR CONTRIBUTIONS

M.H. Abdul Hadi (Data curation; Formal analysis; Investigation; Resources; Software; Visualization; Writing - original draft)

N.A. Ramli (Conceptualization; Methodology; Validation; Writing - review & editing; Supervision)

Q.U.I Islam (Writing - review & editing)

DECLARATION OF ORIGINALITY

The authors declare no conflict of interest to report regarding this study conducted.

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