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A Performance Comparison of LSTM and GRU Architectures for Forecasting Daily Bitcoin Price Volatility

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ABSTRACT

The highly volatile movement of Bitcoin prices requires the use of prediction methods that accurately capture complex, rapidly changing patterns. This study aims to compare the performance of two recurrent neural network architectures, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), in forecasting Bitcoin prices based on historical time series data. The analysis was conducted using daily closing price data, with several parameter configurations applied, including dropout value, learning rate, and number of epochs at a window size of 30. The training process used a univariate approach to assess each model's ability to learn temporal patterns without the influence of external variables. The results indicate that the GRU model consistently outperforms LSTM across most experimental settings. The best performance was achieved with 30 epochs, dropout 0.1, and a learning rate of 0.001, producing RMSE 1478.333, MAE 1000.900, R^2 0.996081, and MAPE 1.973072. These metrics demonstrate a lower error level and a stronger fit to actual Bitcoin price movements. Moreover, a paired t-test confirmed that the performance gap between the two models is statistically significant. Overall, the findings suggest that the Gated Recurrent Unit architecture is more efficient at capturing nonlinear patterns and responding to the volatility of cryptocurrency price fluctuations, making it a promising approach for future predictive modelling of financial time series.

INTRODUCTION

Rapid innovations in financial technology have significantly altered the world's economic systems, particularly through the emergence of digital assets like cryptocurrencies. In recent years, cryptocurrencies have become among the most actively traded financial instruments and have attracted significant attention from academics and investors due to their rapid growth (Ben Hamadou et al., 2025; Boozary et al., 2025; Shirwaikar et al., 2025). Interest in these digital assets continues to rise, including among institutional investors, due to their potential for high returns despite extreme price volatility (Ortu et al., 2022). Cryptocurrency is a digital currency built on blockchain technology and secured through cryptographic mechanisms, making it resistant to fraud and data manipulation (Hamayel & Owda, 2021; Iqbal et al., 2024). Blockchain functions as a decentralised record-keeping system in which encrypted transaction information is maintained across multiple networked computers, enabling direct peer-to-peer exchanges without the need for intermediaries (Bouteska et al., 2024; Seabe et al., 2023; Syed et al., 2024).

Among the various cryptocurrencies circulating in the digital market, Bitcoin is the first and most widely adopted. (Lee, 2024; Parameswaran et al., 2024). Introduced by Satoshi Nakamoto in 2008 and launched in 2009, Bitcoin has grown rapidly and become a benchmark for measuring cryptocurrency market trends. (Boozary et al., 2025; Lee, 2024). In addition to Bitcoin, other digital assets such as Ethereum, Cardano, Tether (USDT), and Ripple (XRP) have emerged, further strengthening the global cryptocurrency ecosystem. (Boozary et al., 2025; Syed et al., 2024). However, Bitcoin's price movement is highly volatile and influenced by multiple factors, including trading volume, public sentiment, shifts in regulatory policy, and broader global economic dynamics. (Akouaouch & Bouayad, 2025; Sujana & Jairam, 2024). This high volatility makes Bitcoin price forecasting both essential and challenging for investors and financial analysts. (Boozary et al., 2025; Kabir et al., 2025).

Conventional statistical models such as ARIMA and GARCH have long been applied to the analysis of financial time-series data. However, these models have limitations because they mainly capture linear relationships and struggle to handle non-stationary, nonlinear, and highly volatile data, such as cryptocurrency prices. (Pinastawa et al., 2025; Piri & Razzagzadeh, 2025). To overcome these limitations, recent studies have shifted toward machine learning and deep learning methods, which are better at recognising nonlinear patterns and complex dynamics in financial data. (Akila et al., 2023; Akouaouch & Bouayad, 2025). Among deep learning architectures, RNN-derived models such as LSTM and GRU are widely used because they can learn long-range temporal dynamics and mitigate vanishing gradients. (Gunarto et al., 2023; Yurtsever, 2021).

Previous research has demonstrated that LSTMs and GRUs outperform traditional models in predictive performance. Studies by (Latif et al., 2023; Pan, 2023) Show that LSTM outperforms ARIMA, achieving an R^2 of 0.9899 as reported in (Piri & Razzagzadeh, 2025), while (Somayajulu et al., 2025) Reports a MAPE of 6.5%. In parallel, GRU has also demonstrated strong research performance. (Pinastawa et al., 2025) Reporting an R^2 value of 0.9717. Although both models have proven effective for cryptocurrency price forecasting, model performance can still be improved through optimised hyperparameter tuning. This research gap highlights the need for further investigation into identifying optimal configurations for these models.

Based on this gap, the present study aims to systematically compare the performance of LSTM and GRU in predicting Bitcoin prices by exploring multiple hyperparameter configurations at a window size of 30. This research employs a univariate approach, using the closing price as the primary variable, to assess each model's ability to learn temporal patterns efficiently, free of external influences. The findings are expected to support the development of more reliable deep learning–based forecasting models and to offer meaningful guidance to investors navigating the highly dynamic and volatile cryptocurrency market.

METHOD

This research method is designed to build and evaluate a Bitcoin price prediction model using LSTM and GRU architectures. The research process is carried out through a series of systematic stages, starting with data collection, preprocessing, data sequence generation, model development, hyperparameter tuning, and performance evaluation using various error metrics.

1. Dataset

This study uses a historical Bitcoin price dataset (BTC-USD) from Yahoo Finance, covering the period from February 5, 2018, to February 1, 2025. Each entry includes six main features: Open (opening price), High (highest price), Low (lowest price), Close (closing price), Volume (amount of assets traded), and Date (time index). However, this study uses a univariate approach, using only the Close feature as the input variable and prediction target. This single-feature selection aims to focus the analysis on the pure temporal pattern of Bitcoin's closing price movement, without being influenced by other variables.

2. Long Short-Term Memory (LSTM)

LSTM is an RNN architecture specifically designed to overcome the vanishing gradient problem. The LSTM architecture has three main gates: the Forget Gate, the Input Gate, and the Output Gate that regulate the flow of information so that the model can store, update, and retrieve long-term information effectively. The complete structure of the information flow in an LSTM can be seen in Figure 1 (Shirwaikar et al., 2025; Wen & Ling, 2023).

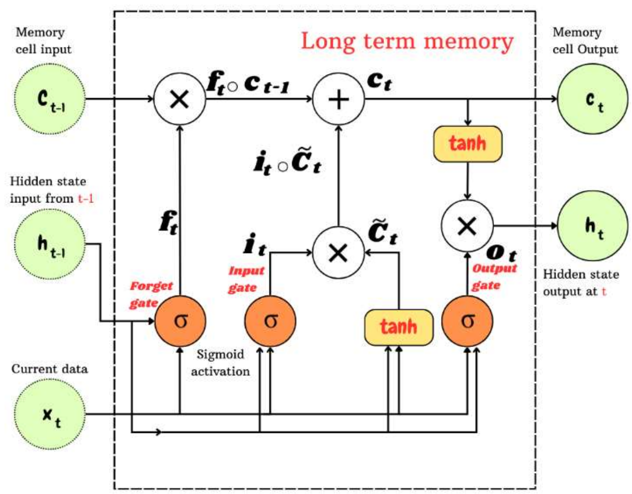

Figure 1. LSTM Architecture

The mathematical equations used in the memory and hidden state update process in LSTM are formulated as follows (1)–(6). (Dip Das et al., 2024; Said, 2025; Yurtsever, 2021):

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$
$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$
$$\tilde{C}_t = tanh\left(W_c\left[h_{t-1}, x_t\right] + b_c\right) \tag{3}$$
$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{4}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$
$$h_t = o_t \odot \tanh\left(c_t\right) \tag{6}$$

3. Gated Recurrent Unit (GRU)

The GRU is a simpler architecture than the LSTM, yet still effective in capturing long-term dependencies in sequential data. Instead of using multiple gates as in an LSTM, the GRU combines the functions of several LSTM gates into two primary gating mechanisms: the update gate and the reset gate. (Syed et al., 2024; Yurtsever, 2021).

The complete GRU architecture is shown in Figure 3 (Dip Das et al., 2024).

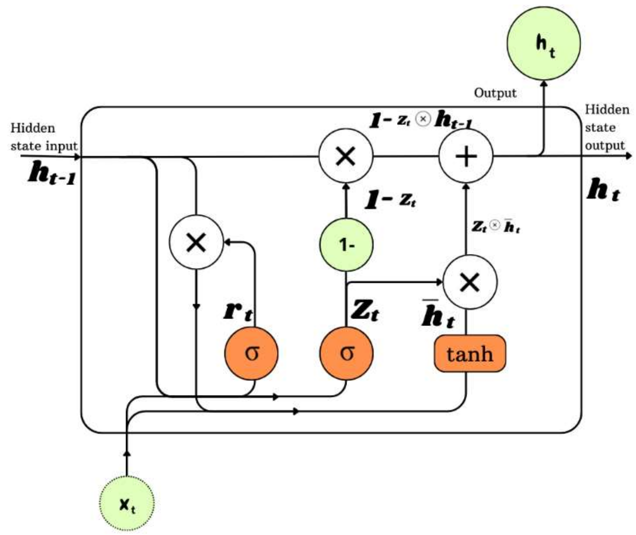

Figure 2. GRU architecture

The mathematical equation for the GRU is formulated as follows (7)–(10) (Yurtsever, 2021):

$$z_t = \sigma \left(W_z \left[h_{t-1}, x_t \right] + b_z \right) \quad (7)$$

$$r_t = \sigma \left(W_r \left[h_{t-1}, x_t \right] + b_r \right) \quad (8)$$

$$\tilde{h}_t = tanh \left(W_h \left[r_t \odot h_{t-1}, x_t \right] + b_h \right) \quad (9)$$

$$h_t = \left(1 - z_t \right) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (10)$$

4. Research Flow Diagram

The flowchart of this research method, as shown in Figure 3, consists of several systematic stages, starting from data upload to analysis of model comparison results. Each stage is explained as follows:

a. Data Upload

In this stage, the researcher uploads a CSV file containing Bitcoin price data. This data serves as the primary source for the entire analysis and predictive modelling process.

b. Data Preprocessing

The preprocessing stage is carried out to ensure good data quality before it is used for model training. This process includes:

- Transforming dates to datetime format (YYYY-MM-DD).
- Sorting data by date chronologically.
- Checking and handling missing values.
- MinMax normalisation, so that all features fall within the range [0, 1].

Normalisation is performed using Equation (11) (Yanimaharta & Santoso, 2025).

$$X\,norm = \frac{X - Xmi}{Xmax - Xmi} \quad (11)$$

Normalisation aims to prevent any single feature from dominating the learning process, enabling the model to learn data patterns optimally. This stage also helps generate stable data ready for use in the deep learning modelling process.

c. Windowing

The normalised data is converted to a sequential form using a 30-day window. This means that the previous 30 closing price data points (Close) are used as input to predict the closing price on the 31st day.

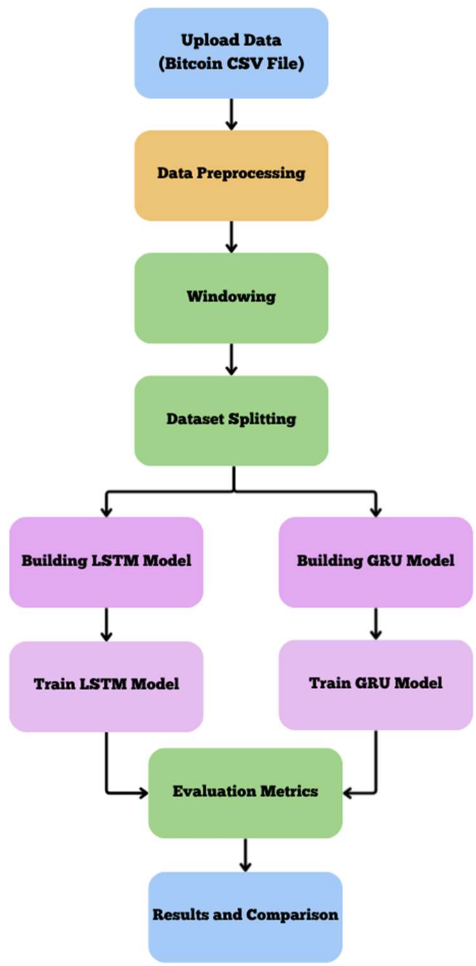

Figure 3. Research Process Flow Diagram

Dataset Splitting

The sequential data set is then divided into two subsets: training data and test data. The division is done chronologically to preserve the original order of the time series data. 70% of the data is used for training, while the remaining 30% is used for testing. This approach ensures the model has enough information to learn historical patterns while still being evaluated on previously unseen data.

d. Building Models (LSTM and GRU)

In this stage, two model architectures are built: LSTM and GRU, each using two main layers with 200 and 100 units, respectively. These architectures are designed to capture long-term patterns and the dynamic fluctuations in Bitcoin prices. The GRU model was used for comparison because it has a simpler structure than the LSTM.

e. Hyperparameter Tuning for LSTM and GRU

Hyperparameter tuning was performed to find the model configuration that provided the best performance. The parameter variations tested included:

Epochs: 10, 30, and 50

Learning rate: 0.001 and 0.0005

Dropout: 0.1 and 0.2

Through these parameter combinations, the researchers aimed to identify the settings that yielded the best performance for the LSTM and GRU models in predicting Bitcoin price movements.

f. Evaluation Metrics

Both models were tested using evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE).

The formula for each metric is shown in Equations (12)–(15) (Dip Das et al., 2024):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (12)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}[y_i - \hat{y}_i] \quad (13)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}) \quad (14)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (15)$$

In this Equation, y_i Is the actual value of the data, while $\hat{y}_i$ Does the model generate the predicted value? The symbol $\bar{y}_i$ represents the average of all actual values, and n Represents the total amount of data used in the model's evaluation.

g. Results and Comparison

The final stage is presenting the evaluation results in a comparison Table and a prediction visualisation graph. The analysis aims to determine which model is more accurate, stable, and capable of providing the best predictions for Bitcoin prices.

RESULTS

1. Model Evaluation (Window Size = 30)

Testing was conducted using two model architectures, LSTM and GRU, with varying dropout parameters (0.1 and 0.2), learning rates (0.001 and 0.0005), and the number of epochs (10, 30, and 50). The complete evaluation outcomes for all configurations are presented in Table 1. Overall, GRU demonstrated more consistent and superior performance compared to LSTM across the majority of hyperparameter combinations. Furthermore, increasing the number of epochs significantly improved performance, particularly from epoch 10 to 30, after which the improvement trend plateaued as the models approached convergence.

Table 1. Evaluation Results for Window Size 30

Model	Dropout	Learning_rate	RMSE	MAE	R²	MAPE
			Epoch 10			
LSTM	0.1	0.001	2811.811	2285.985	0.985824	5.157721
GRU	0.1	0.001	1585.352	1041.637	0.995493	1.99839
LSTM	0.1	0.0005	3111.484	2109.307	0.982641	3.858031
GRU	0.1	0.0005	2075.498	1585.208	0.992276	3.416562
LSTM	0.2	0.001	4333.008	3261.509	0.966336	6.000119
GRU	0.2	0.001	1633.72	1234.33	0.995214	2.775655
LSTM	0.2	0.0005	3895.713	2743.403	0.972788	4.957672
GRU	0.2	0.0005	2734.251	2243.465	0.986595	4.912435
			Epoch 30			
LSTM	0.1	0.001	1708.494	1270.867	0.994766	2.743383
GRU	0.1	0.001	*1478.333*	*1000.9*	*0.996081*	*1.973072*
LSTM	0.1	0.0005	1979.332	1364.84	0.992975	2.669326
GRU	0.1	0.0005	1644.3	1060.051	0.995152	1.98268
LSTM	0.2	0.001	*1698.929*	*1188.504*	*0.994825*	*2.379214*
GRU	0.2	0.001	1600.529	1038.586	0.995407	1.965126
LSTM	0.2	0.0005	2533.568	1659.867	0.988491	2.966577
GRU	0.2	0.0005	2008.611	1324.324	0.992766	2.327899
			Epoch 50			
LSTM	0.1	0.001	2020.030	1388.32	0.992683	2.581175
GRU	0.1	0.001	1627.618	1099.343	0.99525	2.187626
LSTM	0.1	0.0005	2312.098	1544.187	0.990415	2.728593
GRU	0.1	0.0005	1749.104	1121.342	0.994514	2.020896
LSTM	0.2	0.001	1992.349	1270.094	0.992883	2.221581
GRU	0.2	0.001	2637.121	1913.846	0.987531	3.44083
LSTM	0.2	0.0005	1779.882	1189.665	0.99432	2.26253
GRU	0.2	0.0005	1653.951	1058.713	0.995095	1.941743

At epoch 10, both models exhibited relatively fluctuating initial performance, with LSTM showing notably higher error rates in several configurations. For example, with a dropout of 0.1 and a learning rate of 0.001, LSTM recorded an RMSE of 2811.811 and a MAPE of 5.157%, while GRU in the same configuration performed significantly better, with an RMSE of 1585.352 and a MAPE of 1.998%. This indicates that GRU learns time-series patterns faster in the early stages of training. Furthermore, the combination of a low dropout rate (0.1) and a larger learning rate (0.001) helps the GRU avoid overfitting and maintain stability at early epochs. At the same time, LSTM still requires more training iterations to build a stable temporal representation.

When the number of epochs was increased to 30, the performance of both LSTM and GRU models became clear. The models had a longer learning time, allowing them to adjust their weights and capture temporal patterns more effectively. At this stage, GRU achieved the best performance across all experiments with a dropout rate of 0.1 and a learning rate of 0.001, yielding an RMSE of 1478.333 and a MAPE of 1.973%. This parameter combination provided an ideal balance between stability and generalisation, allowing the GRU to avoid overfitting while maintaining sensitivity to price changes. Meanwhile, LSTM also showed significant improvement, particularly at a dropout of 0.2 and a learning rate of 0.001 (RMSE of 1698.929, MAPE of 2.379%), indicating that LSTM requires stronger regularisation to achieve optimal performance. However, despite the improvement, LSTM's performance still could not surpass GRU's.

At epoch 50, the performance of both models began to stabilise, and the improvement in accuracy was no longer significant. This indicates that the model has converged, meaning that further training iterations have little impact on error reduction. GRU still maintains its superiority and continues to produce lower error rates across most configurations. This consistency across GRUs further confirms that the GRU architecture is more efficient at learning nonlinear and volatile time-series patterns, such as cryptocurrency prices.

Overall, the experimental results show that the jump from epoch 10 to epoch 30 produced the most significant improvement, while variations in dropout and learning rate play supporting roles, helping stabilise performance and mitigate overfitting. GRU proved to be the most effective model at a window size of 30, achieving its best performance at epoch 30 with an R^2 of 0.996. The best-performing configurations for both LSTM and GRU are summarised in Table 2, which highlights the optimal parameter settings and their corresponding evaluation metrics.

Table 2. Best Results for LSTM and GRU

Model	Epoch	Dropout	Learning_rate	RMSE	MAE	R²	MAPE
LSTM	30	0.2	0.001	1698.929	1188.504	0.994825	2.379214
GRU	30	0.1	0.001	1478.333	1000.900	0.996081	1.973072

2. Significance Testing

To verify whether the performance gap between LSTM and GRU was meaningful and not due to random fluctuations during training, a paired t-test was used to compare the evaluation metrics produced by both models under the same experimental conditions. The statistical outcomes are presented in Table 3.

Table 3. Paired t-test Results Between Models (LSTM vs. GRU)

Metric	t-statistic	p-value	Description
RMSE	2.6976	0.020746	Significant
MAE	2.4781	0.030677	Significant
R²	-2.3764	0.036734	Significant
MAPE	2.2377	0.046892	Significant

The paired t-test results show that all metrics have p-values below 0.05, indicating statistically significant differences between the two models. The positive t-values for RMSE, MAE, and MAPE suggest that GRU consistently produced lower error rates than LSTM across the tested configurations. Meanwhile, the negative t-value for R^2 indicates that GRU had greater explanatory power in predicting price movements. These results collectively demonstrate that GRU's superior performance is not incidental. Instead, the improvements reflect a systematic advantage of the GRU architecture in capturing temporal dependencies within cryptocurrency price data. In other words, GRU's dominance over LSTM is statistically validated, reinforcing that its performance improvement is both consistent and meaningful.

3. Visualisation of Results

The visualisations in Figures 4 and 5 compare the actual Bitcoin price with predictions from the GRU and LSTM models, using the best configuration at epoch 30. Both models can represent the general price movement pattern, but there are apparent differences in their closeness to the actual value. In Figure 4, the GRU model with the best configuration (dropout 0.1 and learning rate 0.001) produces predictions that closely match the actual values. This is evident from the prediction line, which closely follows the actual line during both uptrends and downtrends. The resulting pattern appears more stable and responsive, reflecting GRU's ability to capture the dynamics of Bitcoin price volatility. This finding is consistent with the low error values in this configuration: RMSE 1478.333, MAE 1000.900, R^2 0.996081, and MAPE 1.973%.

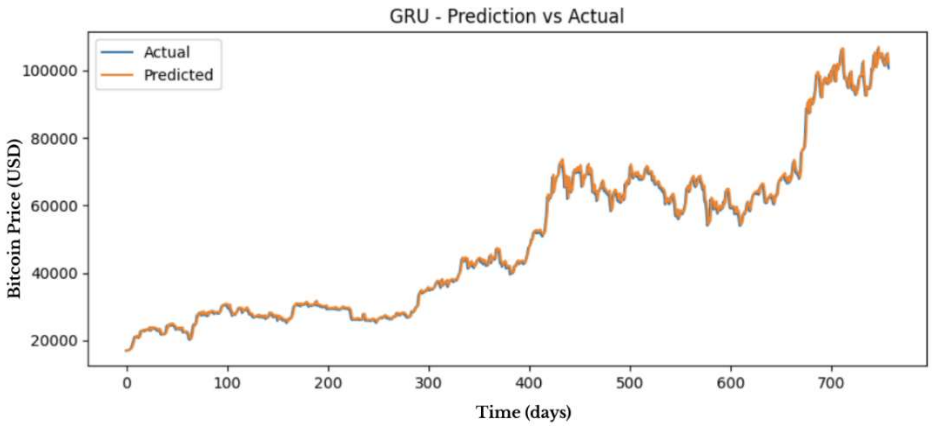

Figure 4. Visualisation of Predictions vs. Actuals of the GRU Model (Epoch 30, Dropout 0.1, Learning Rate 0.001)

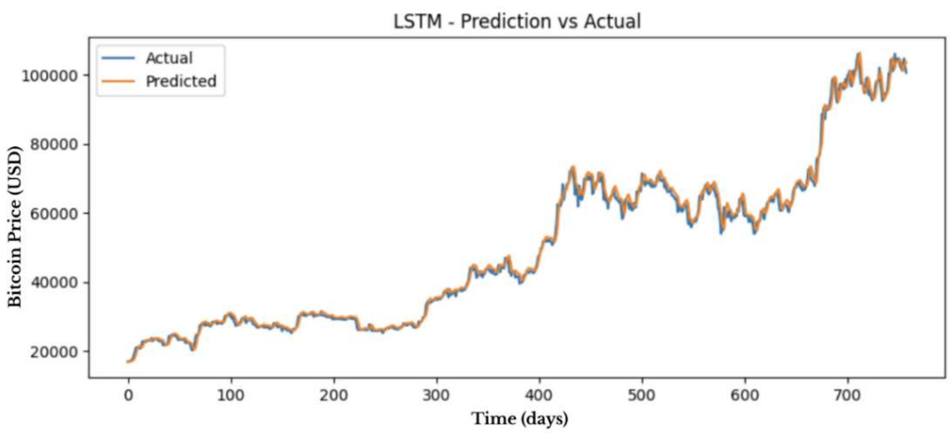

Figure 5. Visualisation of Predictions vs. Actuals of the LSTM Model (Epoch 30, Dropout 0.2, Learning Rate 0.001)

Conversely, Figure 5 shows the performance of the best LSTM model at epoch 30 (dropout 0.2 and learning rate 0.001). Visually, the LSTM prediction also shows a pattern close to the actual values, but at some extreme change points, a slight response delay is observed. This corresponds to slightly higher error values than for GRU, namely RMSE 1698.929, MAE 1188.504, R^2 0.994825, and MAPE 2.379%. Overall, both graphs support the numerical results, which show that GRU provides better prediction accuracy than LSTM at epoch 30. GRU provides a smoother, more stable, and more precise prediction representation, resulting in a visualisation closer to the actual value.

DISCUSSION

Experimental results show that GRU consistently outperforms LSTM at a window size of 30 and various hyperparameter configurations. GRU achieved the best results at epoch 30 with a dropout of 0.1 and a learning rate of 0.001, resulting in an RMSE of 1478.333, an MAE of 1000.900, an R^2 of 0.996081, and a MAPE of 1.973%. Meanwhile, LSTM achieved optimal performance at epoch 30 with a dropout of 0.2 and a learning rate of 0.001, but still exhibited a higher error rate than GRU. This performance difference indicates that the GRU architecture is more efficient at learning patterns in volatile time-series data, such as Bitcoin prices. With only two main gates (update and reset gates), the GRU can learn parameters faster and more stably, especially on datasets with significant dynamic changes. In contrast, LSTMs, with their more complex structure, require stronger regularisation to prevent overfitting and more training iterations to achieve stable performance.

Increasing the number of epochs significantly impacts both models. The most significant performance improvement occurs when the number of epochs increases from 10 to 30, with an apparent decrease in error across all metrics. However, after reaching epoch 30, increasing to epoch 50 shows minimal improvement, indicating that the models have reached convergence. This suggests that epoch 30 is the most efficient training point for both models on this dataset. Paired t-test results confirm that the performance difference between LSTM and GRU is not only numerically significant but also statistically significant. All evaluation metrics yielded p-values < 0.05, indicating that GRU provides consistently better predictive performance and is not due to random variation. This test reinforces the finding that the GRU architecture is better suited to cryptocurrency price prediction tasks characterised by rapidly changing data.

Overall, this study's results confirm that GRU is a more effective model for Bitcoin price prediction with a window size of 30. Furthermore, this study provides important insights into the influence of hyperparameters, such as dropout, learning rate, and number of epochs, on the performance of RNN-based deep learning models. These findings can serve as a basis for developing advanced prediction models and for research focused on optimising time-series models using more efficient neural network architectures.

CONCLUSION

The results show that the GRU model outperforms the LSTM in predicting Bitcoin prices with a window size of 30, as evidenced by its lower error rate and statistically significant test results. This is evident from the best GRU evaluation score, with 30 epochs, a dropout of 0.1, and a learning rate of 0.001, yielding an RMSE of 1478.333, an MAE of 1000.900, an R^2 of 0.996081, and a MAPE of 1.973072. Meanwhile, the best LSTM configuration with 30 epochs, a dropout of 0.2, and a learning rate of 0.001 yields an RMSE of 1698.929, an MAE of 1188.504, an R^2 of 0.994825, and an MAPE of 2.379214, indicating lower performance than the GRU. These findings indicate that the GRU architecture is more efficient and stable at capturing patterns of cryptocurrency price volatility.

However, this study has limitations because it used only univariate data, thereby ignoring external factors such as market sentiment, news, global events, regulatory changes, and technical indicators. These factors have the potential to influence Bitcoin prices significantly and are beyond the scope of the model. Therefore, future research is recommended to develop a more comprehensive approach, for example, by utilising a hybrid RNN model or another deep learning architecture and integrating multivariate data, such as volume, open, high, low, and sentiment, from social media or news. The addition of these external features is expected to improve the model's ability to understand complex market dynamics and produce more accurate cryptocurrency price predictions.

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