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Comparison of ARIMA and GRU Methods in Predicting Cryptocurrency Price Movements

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Abstract: This study compares the effectiveness of the ARIMA and GRU models in predicting Bitcoin price movements, addressing the need for reliable predictive tools amidst the high volatility of the cryptocurrency market. Previous research has highlighted the strengths of each model in financial forecasting: ARIMA for short-term, stationary data and GRU for capturing complex temporal patterns. The purpose of this study is to evaluate which model performs better in the context of Bitcoin price prediction, offering insights for investors to minimize risks and enhance decision-making in this unpredictable market. The research methodology involves applying both models to Bitcoin price data and comparing their accuracy using the Mean Absolute Percentage Error (MAPE) across various forecasting intervals. Results indicate that GRU achieves higher accuracy in long-term forecasts, while ARIMA performs optimally for shorter time frames. However, both models demonstrate limitations, especially as the prediction horizon extends, underscoring the inherent challenges of cryptocurrency price forecasting. These findings suggest that GRU may be better suited for longer investment horizons, while ARIMA remains effective for short-term predictions. The conclusions affirm the potential of using these models selectively to align with specific investment strategies in cryptocurrency markets, although further research is recommended to improve predictive accuracy under evolving market conditions.

Keywords: Bitcoin, price prediction, Arima, GRU, Cryptocurrency.

INTRODUCTION

In recent years, the cryptocurrency market has garnered significant attention within global finance, driven by exponential user growth and pronounced market volatility. Data from Bitfinex reveals that, as of December 1, 2023, the global number of cryptocurrency holders reached 575 million, a substantial increase of 33.1% from 432 million at the beginning of the year.(BITFINEX, 2023) This rapid growth highlights the expanding role of digital assets in modern financial ecosystems. However, cryptocurrencies remain highly volatile, often experiencing price fluctuations far exceeding those observed in traditional financial markets. Studies, including those by Nurul Huda and Risman Hambali, emphasize the high-risk nature of cryptocurrency investments, largely attributable to extreme price volatility and uncertain regulatory environments.(Huda & Hambali, 2020) This volatility, coupled with the market's rapid expansion, underscores the pressing need for accurate and reliable predictive tools to support informed investment decision-making.

Bitcoin, with the largest market capitalization, plays a central role in the cryptocurrency ecosystem. As of December 2024, Bitcoin dominates over 50% of the global market capitalization. Due to Bitcoin's dominance, altcoin price movements tend to follow its patterns, making it the primary indicator of the cryptocurrency market.(Amanintia, 2019)

This study aims to compare two prevalent models for Bitcoin price prediction: the Autoregressive Integrated Moving Average (ARIMA) model and the Gated Recurrent Unit (GRU) neural network. The motivation for this research arises from Bitcoin's unique financial profile, which demands a specialized modeling approach. Its price dynamics are influenced by a complex interplay of technical factors, investor sentiment, and evolving regulatory landscapes. Accurate forecasting in this context is essential, as it creates potential for substantial investment opportunities while also presenting elevated risks. Additionally, Focusing on Bitcoin in this study is relevant due to its significant influence on altcoins and the cryptocurrency market.

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This research seeks to evaluate the performance of ARIMA, a traditional model known for its suitability with stationary financial data, against GRU, a recurrent neural network architecture recognized for its ability to capture complex temporal patterns in non-linear data. Through this comparative analysis, the study intends to contribute valuable insights to the body of literature on cryptocurrency price prediction and provide practical recommendations for stakeholders within the rapidly evolving financial technology sector. This research aligns with the increasing public interest in cryptocurrencies and aims to advance understanding of optimal forecasting methods for Bitcoin, supporting investors in making informed decisions, mitigating risks, and navigating the dynamic landscape of the cryptocurrency market. Ultimately, this study aspires to contribute to a more robust investment framework in a domain marked by rapid innovation and high stakes.

LITERATURE REVIEW

The foundational research for this study was conducted by Nurul Huda, who specifically explored the Risks and Profitability of Cryptocurrency Investments. The findings indicate that cryptocurrency investments have the potential for very high returns. However, it is important to note that such investments also carry significant risk due to extreme market volatility.(Huda & Hambali, 2020) In this context, Nurul Huda's study offers significant insights into the dynamics of cryptocurrency investments, establishing a basis for our research. This drives our desire to undertake research focused on mitigating the substantial risks associated with cryptocurrency investments.

To reduce investment risks in cryptocurrency, various analysis and prediction methods have been applied, as revealed in Ahmad Yunizar’s study, titled "Application of the Gated Recurrent Unit Model in Recurrent Neural Networks for Cryptocurrency Price Prediction." This study shows that the use of the Gated Recurrent Unit (GRU) method delivers impressive accuracy in predicting cryptocurrency price movements, especially for Bitcoin. According to comparisons between actual price data and predictions generated by the GRU method, the study demonstrates significant accuracy rates. Specifically, to predict Bitcoin price movements one month ahead, the GRU model achieved an accuracy of 90.26%. For a six-month horizon, the predictive accuracy was 77.74%, while for a 12-month horizon, the model achieved an accuracy of 75.98%. These findings confirm that the GRU model is a reliable tool for predicting cryptocurrency prices, particularly Bitcoin.(Yunizar et al., 2023) The reliability of the GRU model in this study reinforces the potential of this approach as a valuable tool for investors and market participants to make more informed decisions. With high prediction accuracy, investors can plan their strategies more precisely, minimize risks, and potentially enhance investment returns.

Within the realm of Recurrent Neural Network (RNN) methods, various models are available beyond the Gated Recurrent Unit (GRU), one of which is Long Short-Term Memory (LSTM). A study conducted by Mohammad Rezza Pahlevi is noteworthy, particularly in the context of comparing the LSTM and GRU models in predicting Forex market movements. Interestingly, the results indicate that GRU not only performs well but also outperforms LSTM in Forex prediction contexts.(Pahlevi et al., 2023)

The positive results observed in the comparison between LSTM and GRU provide a strong basis for further research. As technology advances and analytical needs become more complex, continued exploration of deep learning models is essential. By involving additional comparison methods, we can identify the most optimal model for forecasting cryptocurrency market movements with maximum accuracy.

In addition to Recurrent Neural Network (RNN) methods classified under deep learning, other approaches are also worth considering, such as Autoregressive Integrated Moving Average (ARIMA), which belongs to the statistical time series model category. This method has the capability to forecast future values based on patterns and trends in historical data.(ArunKumar et al., 2022) In the study titled "Short Term Prediction on Bitcoin Price Using ARIMA Method," I Made Wirawan demonstrated that ARIMA can predict Bitcoin price movements for periods ranging from one to seven days ahead with satisfactory results. Several models were tested, revealing that the ARIMA model with parameters (4,1,4) provided the highest accuracy in Bitcoin price prediction. The resulting Mean Absolute Percentage Error (MAPE) was 0.87 for the first day (June 1, 2019) prediction and 5.98 for the seventh day (June 7, 2019) prediction.

Wirawan’s research highlights that the ARIMA model tends to perform optimally when predicting short-term price movements, especially for the first two periods ahead. As the number of forecasted periods increases, accuracy tends to decline. Despite significant differences in price over time, ARIMA remains capable of identifying and predicting price change patterns within a seven-period horizon.(Wirawan et al., 2019)

Beyond the context of cryptocurrency price prediction, extensive research has also been conducted on the ARIMA, LSTM and GRU models to assess and compare their performance. A study by Xiaolei Liu focused on short-term wind speed prediction over the ocean. In his research, Xiaolei Liu applied the Seasonal ARIMA approach, which was then compared with GRU and LSTM.(Liu et al., 2021)

The findings of this study indicate that Seasonal ARIMA (SARIMA) demonstrates particular advantages in handling wind speed prediction over the ocean. This approach directly supports seasonal component estimation in univariate datasets, yielding more suitable results. With advancements in technology and increasingly complex analytical approaches, this study provides an in-depth perspective on SARIMA's advantages in addressing prediction challenges in the context of ocean wind speeds. In accounting for the seasonal variations that characterize ocean wind speed, SARIMA has proven to deliver more accurate and relevant results.(Liu et al., 2021)

The findings from previous studies highlighting the capabilities of the GRU, LSTM, and ARIMA methods in cryptocurrency price prediction reveal that all methods can predict cryptocurrency prices. The comparison between GRU and LSTM has demonstrated that GRU outperforms LSTM in cryptocurrency prediction, while for wind speed prediction, ARIMA proved superior when compared with GRU and LSTM. Therefore, a comparative study between GRU and ARIMA in the context of cryptocurrency price prediction becomes increasingly relevant. By evaluating the performance of both methods, this study will compare which method is more effective and reliable in predicting cryptocurrency price movements.

METHOD

The methodology in this study is designed to systematically evaluate the comparative effectiveness of ARIMA and GRU models in predicting Bitcoin price movements. Given the unique volatility and non-linear patterns in the cryptocurrency market, developing a robust methodological approach is essential to ensure accurate and reliable predictions. This approach involves structured steps, from data collection and preprocessing to model implementation and performance evaluation, each tailored to address specific challenges inherent in cryptocurrency forecasting. By following a clear, step-by-step procedure, this methodology aims to provide insights into the relative strengths of ARIMA and GRU for both short-term and long-term price predictions in this high-risk market.

The research methodology flow can be seen in the following figure.

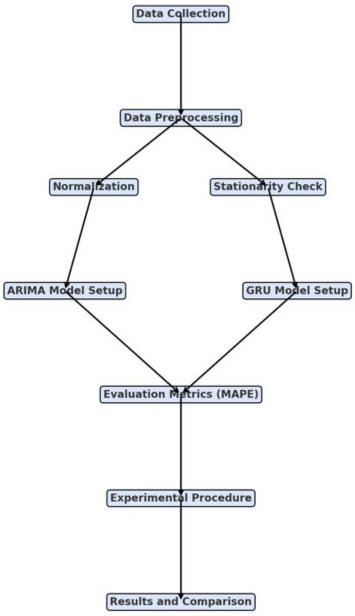


Fig. 1 Research Methodology Flowchart

Research Stages

This process includes several critical stages, each contributing to a comprehensive analysis of the predictive abilities of both models. The following steps outline the methodology used in this study:

Data Collection

The initial step entails collecting historical Bitcoin price data from yahoo finance from January 1, 2022, to January 1, 2023, which will serve as the foundation for training and testing the models. This data is essential as it provides the time-series information required for both ARIMA and GRU models to learn and make predictions.

Data Preprocessing

After collecting the data, it undergoes preprocessing to ensure it is clean and suitable for analysis. This stage involves handling missing values using linear interpolation, organizing the data chronologically, and addressing outliers through the Interquartile Range (IQR) method. These steps prepare the data for model input, ensuring that the models can interpret and use the data accurately.

Normalization and Stationarity Check

Normalization

The data is normalized to a common scale, typically between 0 and 1, to improve the performance of machine learning models, particularly GRU. Normalization allows the GRU model to learn effectively without being affected by the magnitude of values.

Stationarity Check

For the ARIMA model, a stationarity check is performed, as ARIMA requires stationary data for accurate predictions. If the data is non-stationary, transformations like differencing are applied to make it stationary, allowing ARIMA to capture short-term trends more effectively.

Model Setup

ARIMA Model Setup

The ARIMA model is configured by selecting optimal parameters (p, d, q), specifically tuned for short-term price predictions. This tuning process ensures that ARIMA is best equipped to capture trends within shorter time frames.

GRU Model Setup

The GRU model is developed to capture long-term dependencies in data based on time series. Its setup involves structuring the neural network and optimizing hyperparameters such as the number of GRU units, batch size, and learning rate, making it well-suited for complex temporal patterns in the data.

Evaluation Metrics (MAPE, MSE, and R-squared)

The evaluation of prediction accuracy for each model is based on three primary metrics: MAPE (Mean Absolute Percentage Error), R-squared and MSE (Mean Squared Error).

MAPE quantifies the average percentage error between predicted and actual values, providing a reliable measure of each model’s performance in terms of relative accuracy.

MSE measures the average squared difference between predicted and actual values, emphasizing larger errors and providing insight into the overall precision of the predictions.

R-squared indicates the proportion of variance in the actual data that is explained by the model, with higher values signifying a stronger fit to the data. These metrics collectively offer a comprehensive assessment of model performance, capturing both accuracy and the ability to fit the underlying data trends.

Experimental Procedure

Both models undergo training and evaluation using the same dataset but with different prediction intervals (e.g., one month, six months, and twelve months). This step ensures a fair comparison of the models' performance across varying forecasting horizons, allowing us to observe how well each model performs for both short-term and long-term predictions.

Results and Comparison

Finally, the models' performances are analyzed and compared based on their MAPE values across different intervals. This comparison highlights the strengths and limitations of each model, providing insights into their suitability for cryptocurrency price prediction, particularly for Bitcoin.

Theory

Arima

The ARIMA model is a widely recognized statistical approach for forecasting in time-series analysis. It integrates three core elements: AR (Autoregressive), which leverages the relationship between a current observation and a specified number of previous observations (lags), represented by the parameter p; I (Integrated), which applies differencing to the raw data to achieve stationarity in the time series, indicated by the parameter d; and MA (Moving Average), which captures the association between an observation and the residual errors from a moving average model applied to lagged observations, represented by the parameter q.
The general expression for the ARIMA model is:

$$\boldsymbol{y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} + e_t} \quad \textbf{(1)}$$

Where:
y_t represents the observed value at time t,
c denotes a constant term
$\emptyset$ refers to the coefficients associated with the autoregressive (AR) terms,
θ signifies the coefficients related to the moving average (MA) terms,

e_t is the error term at time t,
p, d, and q are the ARIMA model parameters for autoregressive, differencing, and moving average orders, respectively.(Chasipanta & Sánchez-Pozo, 2024)

GRU

The GRU model is a variant of Recurrent Neural Network (RNN) specifically built to process sequential data with long-term dependencies. GRUs are effective in time-series forecasting because they use gating mechanisms to manage information flow through the network, allowing them to capture temporal dependencies in the data.
The GRU cell consists of two main gates:
Update Gate: This gate determines how much of the previous information to pass along to the future.
Reset Gate: This gate determines how much of the past information to forget.

The equations for a GRU cell are as follows:
Update Gate: $z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)$
Reset Gate: $r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$
Candidate Activation (New Memory Content): $\widetilde{h_t} = \tanh(W_h \cdot [r_t * h_{t-1}, x_t] + b_h)$
Final Activation (Hidden State Update):$h_t = (1 - z_t) * h_{t-1} + z_t * \widetilde{h_t}$

Where:
x_t denotes the input at time t,
h_{t-1} represents the earlier hidden state,
h_t indicates the current hidden state.,
z_t represents the update gate,
r_t is the reset gate,
W_z, W_r, W_h are the weights for each gate,
b_z, b_r, b_h are the biases,
σ is the sigmoid activation function,
tanh is the hyperbolic tangent activation function. (Li et al., 2020)

Mean Absolute Percentage Error (MAPE)

MAPE evaluates a predictive model's accuracy by calculating the average percentage difference between predicted and actual values. MAPE evaluates how far the average prediction is from the actual value in relative terms, making it easy to interpret in a percentage context. However, MAPE has a limitation when actual values approach zero, as it can produce infinite or excessively large values.
Formula:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{2}$$

Where:
n = denotes the total number of observations,
y_i = represents the actual value,
$\hat{y}_i$ = stands for the predicted value.
A lower MAPE value indicates a model with higher predictive accuracy, while a higher value suggests less reliable predictions.

Mean Squared Error (MSE)

MSE is an error metric that calculates the average of the squared differences between actual and predicted values. MSE assigns greater weight to larger errors, due to its squared calculation, making it highly sensitive to outliers. MSE is widely used in linear regression and is a common loss function in predictive models.
Formula:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

Where:
n = indicates the total number of observations,
y_i = is the actual value,
$\hat{y}_i$ = denotes the predicted value.
A smaller MSE value reflects a model that better approximates the actual values, while a larger value indicates more significant error between predicted and actual values.

R-squared (R^2)

R-squared (R^2), or the coefficient of determination, measures the proportion of variability in the actual values that can be explained by the predictive model. R-squared values range from 0 to 1, where a value of 1 indicates that the model fully explains the data's variability, while a value of 0 indicates that the model fails to explain any variability in the data.

Formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

Where:
y_i = is the actual value,
$\widehat{y_i}$ = denotes the predicted value,
$\bar{y}$ = represents the mean of actual values,
n = indicates the total number of observations.

A higher R-squared value suggests that the model captures a larger portion of the data's variability, reflecting an improvement in predictive accuracy. A low R-squared value suggests that the model does not capture the data pattern well.(Chicco et al., 2021)

RESULT

This study presents a comparative analysis of the ARIMA and GRU models in predicting cryptocurrency price movements, evaluated over various time intervals (yearly, monthly, weekly, and daily) Using performance indicators such MAPE, MSE, and R-squared to evaluate the level of accuracy of each model.

Data Collection

In this research, historical Bitcoin price data was collected from Yahoo Finance as the primary source, The data for this research was collected across multiple specific time frames to capture both long-term trends and short-term fluctuations in Bitcoin's price. For long-term analysis, a one-year dataset with daily intervals was gathered from January 1, 2022, to January 1, 2023, providing a comprehensive view of broader market trends and yearly price movements. To examine medium-term volatility, a one-month dataset with hourly intervals was collected from December 1, 2022, to January 1, 2023, capturing price fluctuations over a single month. For short-term trends, a one-week dataset with hourly intervals was compiled from December 25, 2022, to January 1, 2023, focusing on price movements during a period of high market activity. Lastly, for ultra-short-term analysis, a one-day dataset with hourly intervals was obtained from December 31, 2022, to January 1, 2023. This multi-granularity data set enables a detailed examination of Bitcoin's price fluctuations over different time scales, offering a robust foundation for training and evaluating both ARIMA and GRU models. By using data across various timeframes, we ensure that the models can be assessed not only for short-term volatility but also for their ability to capture long-term trends. This approach is crucial in capturing the unique and dynamic patterns typical of the cryptocurrency market, providing a strong basis for predictive accuracy in our experiments.

Fig. 2 Bitcoin Price

Data Preprocessing

The initial Bitcoin price data undergoes a series of preprocessing steps to ensure it is clean and well-structured for analysis. This process includes handling any missing values by employing techniques linear interpolation.(Che et al., 2024) Outliers are addressed by applying logarithmic transformations to reduce the impact of extreme values while preserving the underlying patterns in the data. This approach ensures that significant price fluctuations, which are common in Bitcoin price data, are smoothed out without losing valuable temporal trends. Additionally, statistical methods like interquartile range (IQR) are employed to identify and handle outliers, ensuring data consistency and reliability. Additionally, the dataset is examined for inconsistencies, such as duplicate entries or errors in the chronological order, which are corrected to preserve the integrity of the time series.(Fan et al., 2021) Min-Max scaling is applied to normalize the data for the GRU model, ensuring a consistent input range that facilitates effective learning. For ARIMA, a stationarity check is performed as it is essential for accurate modeling. Transformations such as differencing or logarithmic adjustments are applied to address non-stationarity, as shown in Fig. 3. These preprocessing steps collectively ensure that the dataset is clean, organized, and optimized for model input stages, enabling reliable training and testing for both ARIMA and GRU models. (Fan et al., 2021; Majka, 2024)

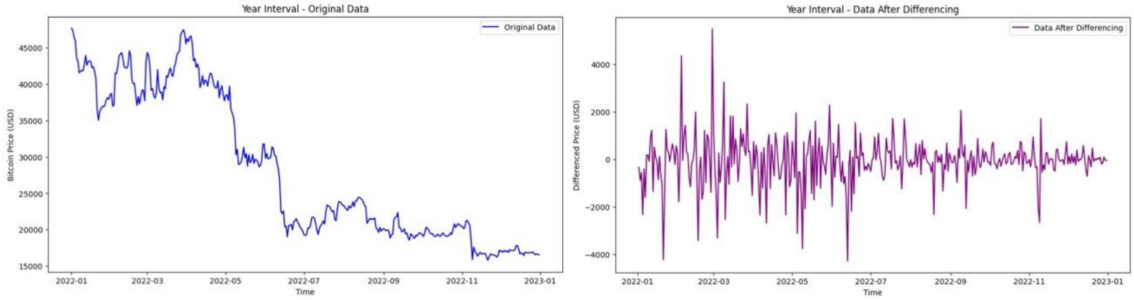


Fig. 3 Differencing Data for Arima

Model Setup

ARIMA Model Setup

The ARIMA model was established utilizing the auto_arima algorithm from the library of pmdarima to ascertain optimal parameters (p, d, q) for each temporal interval, encompassing yearly, monthly, weekly, and daily data. For this purpose, data was differenced where necessary to achieve stationarity, as shown in Figure 3. The best parameters were identified by minimizing the Akaike Information Criterion (AIC) for each interval, ensuring a finely tuned ARIMA model tailored to short-term trends in Bitcoin prices. By using auto_arima, the model configuration could adapt to each dataset's specific characteristics, providing a solid foundation for capturing Bitcoin's daily price fluctuations. After the optimization process, the auto_arima algorithm selected p, d, q values of 1, 0, 0 as the optimal configuration for the dataset analyzed.

For each time interval, the model was trained on a split dataset (80% training and 20% testing) and evaluated based on R-squared metrics, MSE, and MAPE. This setup allowed ARIMA to focus on short-term prediction accuracy, effectively addressing the high-frequency volatility typical of cryptocurrency markets.

GRU Model Setup

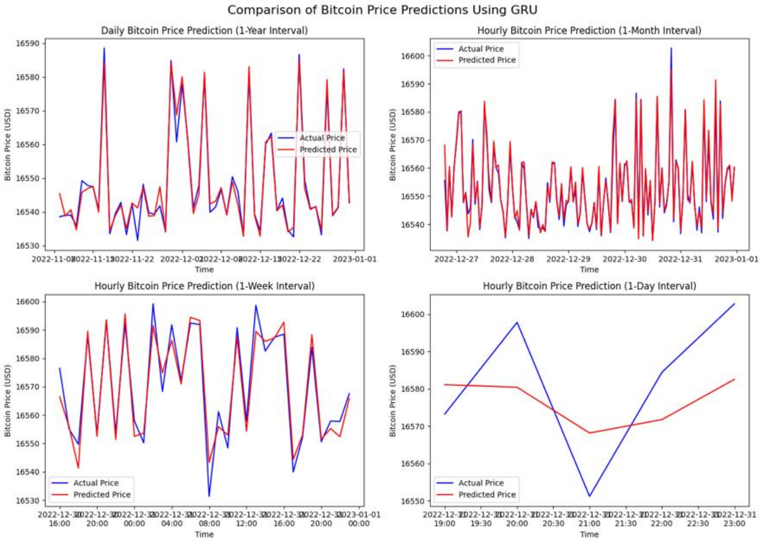
The GRU model was designed to capture long-term dependencies within the Bitcoin price data, focusing on non-linear patterns that are common in financial time series. This involved preparing data with specific time steps for each interval, using Min-Max scaling to normalize values between 0 and 1, which improved the model's learning efficiency. For sequence generation, distinct time steps were chosen to reflect the granular patterns in each time interval.

The GRU architecture consisted of two GRU layers with 50 units each, followed by two dense layers for enhanced prediction accuracy. Key hyperparameters, such as batch size (32) and epoch count (20), were tuned for optimal performance. Each GRU model was trained on an 80-20 train-test split, reshaping data inputs to fit the model's requirements. Predictions were evaluated against actual values using MSE, MAPE, and R-squared metrics, providing insights into the GRU's suitability for both long-term and short-term price forecasting in volatile markets.

This combined setup of ARIMA for short-term trends and GRU for long-term dependencies offers a balanced approach, allowing for a comprehensive comparison of the predictive capabilities of each model in the context of Bitcoin price forecasting.

Experimental Results and Analysis

Both ARIMA and GRU models were optimized separately for each time interval, with the ARIMA model parameters selected based on minimized Akaike Information Criterion (AIC)(Rahman et al., 2022) and the GRU model trained over 20 epochs. The summarized results are presented below:


Comparison of Bitcoin Price Predictions Using GRU

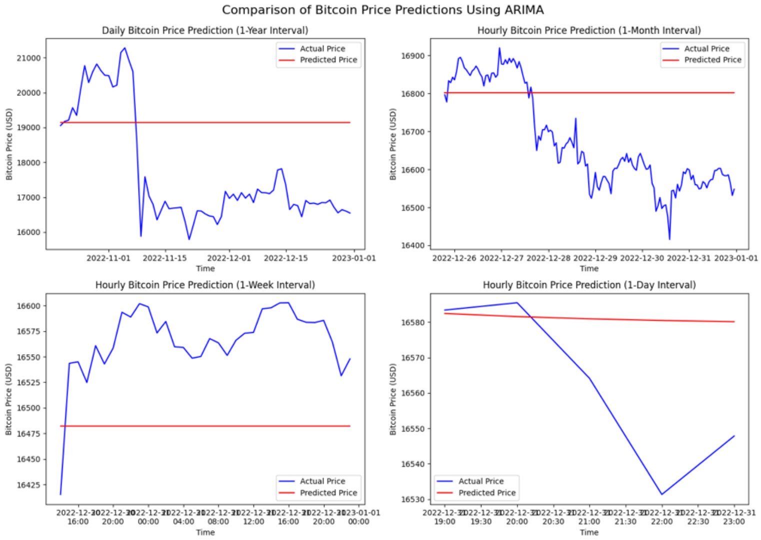
Daily Bitcoin Price Prediction (1-Year Interval)

Hourly Bitcoin Price Prediction (1-Month Interval)

Hourly Bitcoin Price Prediction (1-Week Interval)

Hourly Bitcoin Price Prediction (1-Day Interval)

Fig. 2 Comparison of Bitcoin Price Predictions Using GRU


Comparison of Bitcoin Price Predictions Using ARIMA

Daily Bitcoin Price Prediction (1-Year Interval)

Hourly Bitcoin Price Prediction (1-Month Interval)

Hourly Bitcoin Price Prediction (1-Week Interval)

Hourly Bitcoin Price Prediction (1-Day Interval)

Fig. 3 Comparison of Bitcoin Price Predictions Using ARIMA

Table 1
Comparative Performance of Models Across Different Time Intervals

Time Interval	Model	MSE	MAPE	R-Squared
Year	ARIMA(1,0,0)	4.549.062,90	0,1165	-0,7967
	GRU	5,41	9,37E-05	0,979
Month	ARIMA(0,1,1)	32.457,50	0,0095	-0,9512
	GRU	5,4	9,17E-05	0,9717
Week	ARIMA(0,1,1)	8.116,70	0,0053	-6,1567
	GRU	23,07	2,28E-04	0,9373
Day	ARIMA(1,0,0)	750,2	0,0012	-0,743
	GRU	226,75	0,0009	0,3363

DISCUSSIONS

This study presents valuable insights into the effectiveness of ARIMA and GRU models in predicting Bitcoin price movements across various time intervals (yearly, monthly, weekly, and daily). Based on the evaluation metrics MSE, MAPE, and R-squared it is evident that the GRU model generally outperforms ARIMA in handling cryptocurrency price patterns, for both long-term and short-term predictions.

Overall, the GRU model demonstrated significant advantages across all time intervals, including the daily interval, where ARIMA would typically perform better on stationary or seasonal data.(Nkongolo, 2023) The very low MAPE values of GRU (e.g., 9.37E-05 for the yearly interval) indicate that it can predict prices with minimal percentage error, reflecting a high level of accuracy in modeling Bitcoin prices. Additionally, the R-squared values close to 1 for GRU in the yearly and monthly intervals (0.979 and 0.9717, respectively) show that this model can explain much of the variability in the data, underscoring a strong fit to Bitcoin price patterns.

In the daily interval, GRU continued to outperform ARIMA. The MSE for GRU (226.75) is lower than that of ARIMA (750.2), indicating that GRU provides more accurate predictions at the daily level. Furthermore, the positive R-squared value for GRU (0.3363), as compared to the negative R-squared for ARIMA (-0.743), suggests that GRU is more capable of capturing the variability in daily Bitcoin prices. This finding implies that, although ARIMA is often effective for data with strong seasonal patterns, it is less suitable for highly volatile and non-stationary data like Bitcoin prices.

The superior performance of GRU in this study is mainly due to its recurrent architecture, which allows the model to retain information from previous data sequences, making it more adept at handling long-term patterns and the short-term fluctuations typical of cryptocurrency prices. The recurrent structure of GRU makes it well-suited for data with strong temporal dependencies and non-linear patterns, which are key characteristics of cryptocurrency data.(Patel et al., 2022) GRU’s ability to capture both long-term and short-term patterns simultaneously makes it more flexible and adaptive to the highly volatile dynamics of cryptocurrency markets.

On the other hand, ARIMA has limitations in handling volatility and complex non-linear patterns. ARIMA is a model traditionally designed for stationary data and tends to perform well on data with clear seasonality or regularity, such as economic or weather data, where recurring patterns can be modeled with seasonal components or stable differencing. However, in highly volatile Bitcoin price data, which lacks clear seasonality, ARIMA struggles to provide accurate predictions. The negative R-squared values across most time intervals indicate that ARIMA is ineffective at explaining Bitcoin price variability. This is especially evident in the weekly interval, where ARIMA’s R-squared value of -6.1567 highlights its inability to capture the fluctuating trends within this data.

In practical applications, these results suggest that model selection should be tailored to the characteristics of the data and the specific prediction objectives. For stationary or seasonal data, ARIMA might be an efficient choice, as it is designed to capture seasonal or short-term trends. However, for non-stationary data without clear seasonal patterns, such as cryptocurrency prices, deep learning models like GRU are recommended due to their ability to capture long-term dependencies and complex non-linear patterns.

CONCLUSION

This study concludes that the GRU model is generally more effective than the ARIMA model for predicting Bitcoin price movements across various time intervals, including yearly, monthly, weekly, and daily. The results indicate that GRU outperforms ARIMA in terms of accuracy, as evidenced by lower MAPE values and higher R-squared values across most intervals. GRU's recurrent structure enables it to capture both long-term dependencies and short-term fluctuations, making it well-suited for the highly volatile and non-linear nature of cryptocurrency data. In contrast, ARIMA, traditionally effective for stationary or seasonal data, struggles to accurately model Bitcoin prices due to its inherent limitations in handling volatility and complex non-linear patterns.

While GRU shows promise in improving prediction accuracy, this study highlights several areas for further research. First, GRU's higher computational demands and extended training times pose challenges, particularly for large-scale or real-time applications. Future studies could explore more computationally efficient variants of recurrent neural networks, such as LSTM, or hybrid models that leverage ARIMA for short-term, seasonally predictable trends and GRU for long-term dependencies.

The potential applications of this research extend to financial institutions, investors, and analysts who seek accurate models for forecasting cryptocurrency price movements. A more accurate predictive model can provide insights that support better decision-making in the volatile cryptocurrency market. However, this study’s findings are based on Bitcoin price data alone, limiting the generalizability of results to other cryptocurrencies or asset classes with different volatility profiles. Future research could expand this study to include other types of cryptocurrencies or even traditional financial assets to assess the broader applicability of GRU models.

In summary, while the GRU model demonstrates significant advantages for cryptocurrency price forecasting, further refinement in model efficiency and exploration of hybrid approaches could enhance predictive performance in highly volatile markets.

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