International Journal of Industrial Engineering and Operational Research (IJIEOR)

Contents lists available at IJIEOR
International Journal of Industrial Engineering and Operational Research
journal homepage: http://ijieor.ir
Volume 7, No. 2, 2025

Predicting Solana Cryptocurrency Prices in 2024: A Comparative Study of LSTM and GRU Models

Ali Pirkhedri [a]

[a] *Department of Computer Engineering , Islamic Azad University, Marivan Branch, Marivan, Iran.*

ARTICLE INFO

Received: 2025/02/02

Revised: 2025/03/10

Accept: 2025/04/23

Keywords:

Solana, LSTM, GRU, Cryptocurrency, CoinMarketCap.

ABSTRACT

In this paper, we aim to predict and compare the price of cryptocurrency Solana (SOL) in 2024, using Long ShortTerm Memory (LSTM) and Gated Recurrent Unit (GRU) which are recurrent neural networks. Daily price data for Solana was collected from the CoinMarketCap website over a one-year period, from January 1 to December 30, 2024. The significance of accurate Solana price prediction is emphasized in this study, as Solana's price has a substantial impact on the prices of meme coins within its ecosystem. Specifically, Solana's price fluctuations influence meme coin prices with a time lag, and predicting Solana's price can provide critical signals for forecasting trends in the meme coin market. The LSTM and GRU models were trained using time windows of 10 days to capture short-term and medium-term dependencies in price trends. The performance of the models was evaluated using RMSE (Root Mean Square Error), MAE (Mean Absolute Error) and R^2 (Coefficient of Determination). The results demonstrate that the LSTM and GRU models can predict Solana's price trends with a relatively high degree of accuracy, offering valuable insights for investors and analysts.

1. Introduction

Cryptocurrency markets have become a focal point of interest due to their high volatility and potential for significant returns. However, the unpredictable nature of these markets makes accurate price prediction a challenging yet essential task for investors and traders. Traditional forecasting techniques, such as time-series analysis and statistical models, have been commonly

[a] Corresponding author email address: alipirkhedri@gmail.com (Ali Pirkhedri).
Available online 04/24/2025

2676-3311/BGSA Ltd.

used to predict cryptocurrency prices, but these methods often struggle to capture the complex, non-linear patterns present in cryptocurrency data [4, 16, 14, 11]. To address this issue, machine learning and deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for cryptocurrency price prediction. LSTM, a type of recurrent neural network (RNN), is specifically designed to handle sequential data and capture long-term dependencies, making it well-suited for time-series forecasting [9]. These models have proven to be highly effective in predicting stock market prices, including cryptocurrencies, by processing large volumes of historical data and recognizing temporal patterns that traditional models may overlook [18].

By utilizing past price data, LSTM models are able to forecast future price movements with greater accuracy and reliability. LSTM networks are specifically designed to handle sequential data, making them suitable for modeling time dependent financial data, including cryptocurrencies [15]. Recent studies have demonstrated the effectiveness of LSTM in capturing market dynamics and predicting price trends [2]. Moreover, hybrid models that combine LSTM with attention mechanisms or other advanced methods have further improved prediction accuracy. These advancements highlight the growing importance of deep learning techniques in addressing the challenges of cryptocurrency price prediction. The hybrid models combining LSTM with other machine learning techniques can significantly improve prediction accuracy [5, 13].

Additionally, research has explored the use of alternative deep learning architectures and optimization techniques to further enhance cryptocurrency price forecasting [21]. The Gated Recurrent Unit (GRU) is a powerful recurrent neural network (RNN) designed to handle sequential data efficiently, making it well-suited for tasks like time series forecasting. In cryptocurrency price prediction, GRU stands out for its ability to learn long-term dependencies, capture trends in volatile markets, and adapt to dynamic price movements. By leveraging historical features such as opening price, high, low, volume, and market capitalization, GRU can effectively predict closing prices. With its simpler architecture compared to LSTM, GRU trains faster while delivering comparable performance, making it an excellent choice for forecasting Solana’s price in this study [19, 13, 8].

Artificial intelligence (AI)-based methods, such as LSTM, have gained significant popularity in the field of cryptocurrency price prediction due to their ability to adapt to rapidly changing market conditions and provide more accurate forecasts compared to conventional methods [1, 6].

Integrating deep learning techniques with technical indicators has been shown to improve the predictive performance of models in the cryptocurrency market [17]. The flexibility of AI models allows them to consider various factors, such as market sentiment, historical price trends, and trading volumes, thereby producing more robust and dependable predictions [7, 10]. In the case of Solana (SOL), a rapidly growing cryptocurrency in 2024, accurate price prediction is crucial. Solana's increasing adoption, driven by low transaction fees and a thriving ecosystem, has made it a key player in the cryptocurrency space. Predicting Solana's price is not only vital for understanding its own market dynamics but also for anticipating trends in the broader Solana ecosystem, including meme coins that are closely tied to Solana's price movements [12, 3, 20].

2. Methodology

This section outlines the methodology for predicting SOL prices using LSTM and GRU models. The approach includes data collection, preprocessing, model design, training, and evaluation.

2.1 Data Collection

Daily open, high, low, volume, market capitalization, and close prices of Solana (SOL) from January 1, 2024, to December 30, 2024, were sourced from CoinMarketCap website (*https://coinmarketcap.com/currencies/solana/historicaldata/*). The dataset was reversed to ensure chronological order for accurate sequential learning.

2.2 Data Preprocessing

The collected data is preprocessed to ensure it is in a suitable format for training the model. First, the timestamps are extracted, and the OPEN prices are isolated. To ensure that the model performs well, we apply normalization using MinMaxScaler to scale the prices to a range between 0 and 1. This normalization is critical because LSTM and GRU models are sensitive to the scale of input data, and it helps improve model convergence during training. Next, we construct time series sequences, where each sequence represents a sliding window of past price data used to predict the next price in the sequence. In this study, sliding windows of 10 days were used to create sequences, where each sequence represents historical prices used to predict the next day's closing price.

2.3 Model Design

Two architectures were implemented:

• LSTM: A single LSTM layer with 100 units and ReLU activation, followed by a dense output layer.

• GRU: A single GRU layer with 100 units and ReLU activation, followed by a dense output layer.

Both models were trained using the Adam optimizer and Mean Squared Error (MSE) loss function for 70,90 ,100 and 150 epochs with a batch size of 32.

2.4 Training and Testing

The dataset is split into two parts: 80% for training and 20% for testing. The training data is used to teach the model to recognize patterns in historical price data, while the testing data is used to evaluate how well the model can predict future prices. The model is trained on the normalized data, and the predictions are made on the test set, after which the predicted prices are inverse-transformed back to the original scale using the inverse of the MinMaxScaler.

2.5 Evaluation Metrics

Performance was evaluated using the following metrics:

- **Root Mean Squared Error (RMSE):** Measures the average error magnitude.
- **Mean Absolute Error (MAE):** Indicates the average absolute error.
- **R-squared (R^2):** Represents the variance explained by the model.

The results of these evaluations will be presented in Table. 1 to visually compare the performance of the model under different configurations.

3. Results and Discussion

The Figures 1- 4 illustrate the performance of GRU and LSTM models at different epoch configurations (70, 90, 100, and 150 epochs) for time-series forecasting. Each subplot compares the predicted prices with the actual prices over a specific time period. The LSTM model predictions (red line) also follow the actual prices (blue line) closely. The model benefits from increased epochs, with the 90-epoch configuration showing better adherence to price fluctuations compared to 70 epochs. The LSTM predictions further improve with 100 and 150 epochs. The higher epoch counts result in better trend capturing and reduced prediction error. The GRU model predictions (green line) closely align with the actual prices (blue line), showing improved performance as the number of epochs increases. For 90 epochs, the predictions are smoother and exhibit less deviation from the actual values. With more epochs, the GRU model demonstrates higher accuracy and consistency in capturing price trends. The alignment between predicted and actual prices becomes even more precise. Overall, the figures highlight the progressive improvement in prediction accuracy for both GRU and LSTM models as the number of training epochs increases. The GRU model slightly outperforms the LSTM in terms of capturing finer details in the trends, especially at higher epoch configurations.

The results presented in Table. 1 provide insights into the performance of LSTM and GRU models based on three metrics: MAE, R^2, and RMSE. Below is the detailed analysis:

3.1 Mean Absolute Error (MAE)

• **LSTM:** MAE decreases as the number of epochs increases, starting from 9.017 at 70 epochs and reducing to 7.016 at 150 epochs. This indicates improved prediction accuracy with more training.

• **GRU**: Similarly, GRU shows a decreasing MAE trend, from 7.336 at 70 epochs to 6.323 at 150 epochs. GRU consistently achieves lower MAE than LSTM, demonstrating better accuracy.

3.2 R-Squared (R^2)

• **LSTM:** The R^2 value improves from 0.879 at 70 epochs to 0.922 at 150 epochs, showing that LSTM explains more variance in the data as training progresses.

• **GRU:** GRU also shows a similar improvement in R^2, increasing from 0.913 at 70 epochs to 0.935 at 150 epochs. GRU outperforms LSTM in R^2 across all epochs, indicating better alignment with actual data.

3.3 Root Mean Square Error (RMSE)

• **LSTM:** RMSE decreases from 11.154 at 70 epochs to 8.964 at 150 epochs, reflecting improved prediction performance.

• **GRU:** RMSE for GRU also decreases, from 9.498 at 70 epochs to 8.209 at 150 epochs. GRU consistently achieves lower RMSE than LSTM, demonstrating reduced prediction error.

3.4 Overall Comparison Between LSTM and GRU

• **GRU performs better:** GRU outperforms LSTM in all metrics (MAE, R^2 , RMSE), making it a better choice for the given data.

• **Effect of Epochs:** Increasing the number of epochs improves the performance of both models. However, GRU shows a more significant improvement in MAE and R^2 compared to LSTM.

Table 1. Performance Metrics for LSTM and GRU Models

Method	Epochs	(Mean Absolute Error)	(R-Squared)	(Root Mean Square Error)
LSTM	70	9.017	0.879	11.154
	90	7.926	0.896	10.358
	100	7.049	0.914	9.414
	150	7.016	0.922	8.964
GRU	70	7.336	0.913	9.498

Method Epochs	(Mean Absolute Error)	(R-Squared)	(Root Mean Square Error)
90	6.538	0.931	8.421
100	6.370	0.932	8.400
150	6.323	0.935	8.209

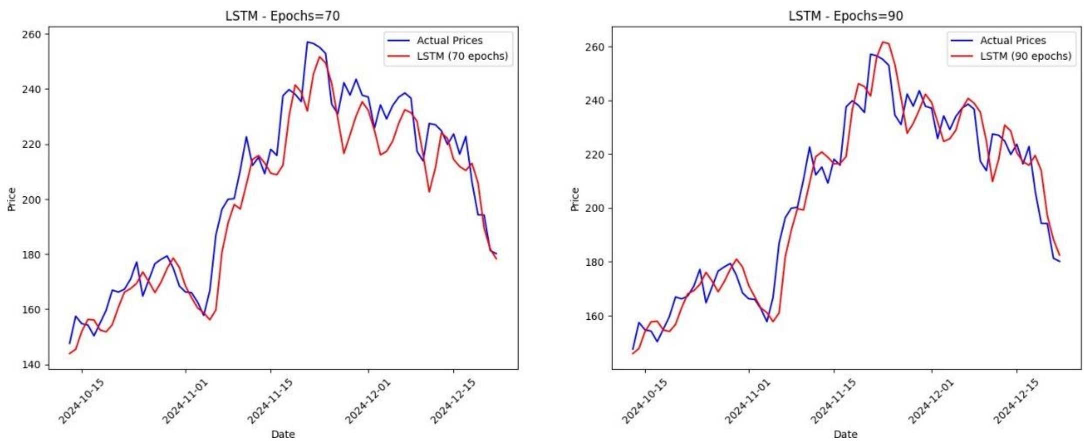

Figure 1. Actual vs. Predicted Prices for LSTM Model (Epoch = 70, 90).

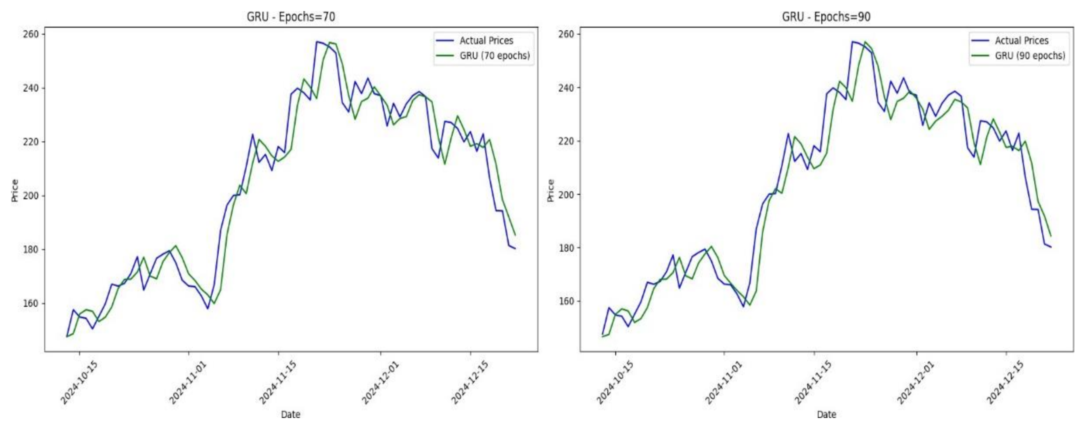

Figure 2. Actual vs. Predicted Prices for GRU Model (Epoch = 70, 90).

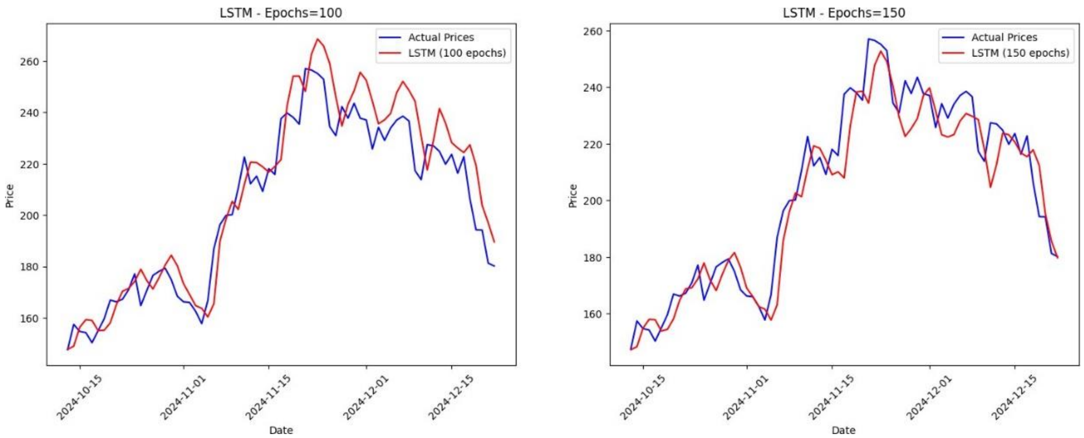

Figure 3. Actual vs. Predicted Prices for LSTM Model (Epoch = 100, 150).

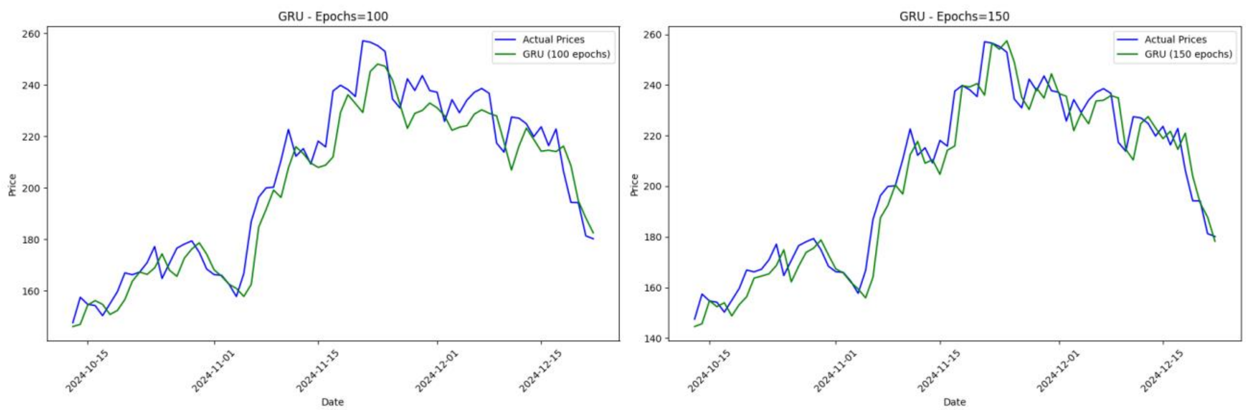

Figure 4. Actual vs. Predicted Prices for GRU Model (Epoch = 100, 150).

4. Conclusion

In this study, the price prediction of the cryptocurrency Solana (SOL) in 2024 was examined using two Recurrent Neural Network (RNN) models, LSTM and GRU. The results showed that both models were capable of predicting the price trend of Solana with relatively high accuracy. The performance of these two models was compared based on various metrics such as Mean Absolute Error (MAE), R-squared (R^2), and Root Mean Squared Error (RMSE). The results indicated that the GRU model outperformed the LSTM model. Specifically, GRU showed superior performance across all evaluation metrics (MAE, R^2, RMSE) and provided more accurate predictions. Furthermore, increasing the number of epochs resulted in significant improvements in prediction accuracy for both models. Particularly, with higher numbers of epochs (100 and 150 epochs), prediction accuracy improved for both models. Considering the better performance of the GRU model compared to LSTM, it can be concluded that GRU is a more suitable option for price prediction of Solana in this study. These results can be valuable for analysts and investors in the cryptocurrency market, especially in predicting price trends of Solana and other related digital assets. Future research directions could explore the incorporation of additional features, such as technical indicators, social media sentiment, and news sentiment, to further enhance the model's predictive power.

References

[1] Alessandretti, L., ElBahrawy, A., Aiello, L. M., and Baronchelli, A. (2018). Anticipating Cryptocurrency Prices Using Machine Learning. Complexity, 8983590:1.

[2] Aldi, M. W. P., Jondri, J., and Aditsania, A. (2018). Analisis Dan Implementasi Long Short-Term Memory Neural Network Untuk Prediksi Harga Bitcoin. eProceedings Eng., vol. 5, no. 2.

[3] Ashraf, M., and Heavey, C. (2023). A Prototype of Supply Chain Traceability using Solana as Blockchain and IoT. Procedia Computer Science, vol. 217, p. 948.

[4] Chan, S., Chu, J., Nadarajah, S., and Osterrieder, J. (2017). A Statistical Analysis of Cryptocurrencies. Journal of Risk and Financial Management, vol. 10, no. 2, p. 12.

[5] Hamayel, M. J., and Owda, A. Y. (2021). A Novel Cryptocurrency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms, AI, vol. 2, no. 4, p. 477.

[6] Jay, P., Kalariya, V., Parmar, P., Tanwar, S., Kumar, N., and Alazab, M. (2020). Stochastic Neural Networks for Cryptocurrency Price Prediction. IEEE Access, vol. 8, p. 82804.

[7] Kanji, A. M., Chaudhary, I., Shankar, R. L., and Srinivasa, G. (2022). Predicting the Price Direction of Bitcoin Using Twitter Data and Machine Learning. in Proc. 2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA), pp. 46-52.

[8] Kim, J., Kim, S., Wimmer, H., and Liu, H. (2021). A Cryptocurrency Prediction Model Using LSTM and GRU Algorithms. in Proc. 2021 IEEE/ACIS 6th International Conference on Big Data, Cloud Computing, and Data Science (BCD), Zhuhai, China, pp. 37-44, doi: 10.1109/BCD51206.2021.9581397.

[9] Krishna, B. M., Sapthami, I., Banka, V. R., and Ravela, C. (2023). Cryptocurrency Price Prediction using Long Short Term Memory Method in Machine Learning. in Proc. 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, pp. 468-471.

[10] Murray, K., Rossi, A., Carraro, D., and Visentin, A. (2023). On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning Deep Learning and Ensembles. Forecasting, vol. 5, p. 196.

[11] Poongodi, M., and Chilamkurti Vijayakumar, N. (2021). Bitcoin Price Prediction using ARIMA Model. International Journal of Web Based Communities, p. 1.

[12] Pierro, G. A., and Tonelli, R. (2022). Can Solana be the Solution to the Blockchain Scalability Problem? in Proc. 2022 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER), Honolulu, HI, USA, pp. 1219-1226.

[13] Seabe, P. L., Moutsinga, C. R. B., and Pindza, E. (2023). Forecasting Cryptocurrency Prices Using LSTM GRU and Bi-Directional LSTM: A Deep Learning Approach. Fractal and Fractional, vol. 7, no. 2, p. 203.

[14] Y. Si, Y. (2022). Using ARIMA model to analyse and predict bitcoin price. BCP Business and Management, vol. 34, p. 1210.

[15] Tanwar, A., and Kumar, V. (2022). Prediction of Cryptocurrency prices using Transformers and Long Short-term Neural Networks, in Proc. 2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP), pp. 1-4.

[16] U, S. K., Aanandhi, S. P., Akhilaa, S. P., Vardarajan, V., and Sathiyanarayanan, M. (2021). Cryptocurrency Price Prediction using Time Series Forecasting (ARIMA), in Proc. 2021 4th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), pp. 598-602.

[17] Wang, J., and Wang, J. (2015). Forecasting stock market indexes using principal component analysis and stochastic time effective neural networks. Neurocomputing, vol. 156, p. 68

[18] Wu, C. H., Lu, C. C., Ma, Y. F., and Lu, R. S. (2018). A New Forecasting Framework for Bitcoin Price with LSTM, in Proc. 2018 IEEE International Conference on Data Mining Workshops (ICDMW), pp. 168-175.

[19] Yamak, P. T., Liu, Y., and Gadosey, P. K. (2019). A Comparison between ARIMA, LSTM, and GRU for Time Series Forecasting, in Proc. 2nd International Conference on Algorithms, Computing and Artificial Intelligence, Sanya, China, pp. 49–55.

[20] Yakovenko, A. (2018). Solana: A new architecture for a high performance blockchain v0.8.13. Whitepaper, 2018.

[21] Yao, D., and Yan, K. (2024). Time series forecasting of stock market indices based on DLWR-LSTM model. Finance Research Letters, vol. 68, 105821.