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# Comparative Analysis of Deep Learning Models for Cryptocurrency Price Predictions: Evidence Based on Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Solana (SOL)

**Adedeji Daniel Gbadebo**
Walter Sisulu University, South Africa
E-mail: agbadebo@wsu.ac.za
ORCID: https://orcid.org/0000-0002-1929-3291
https://ror.org/02svzjn28

**Abstract.** This research examines deep-learning and machine-learning models for cryptocurrency price prediction, with a keen focus on Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Solana (SOL). Cryptocurrencies exhibit high volatility, non-linear behavior and are able to react strongly to exogenous events, making their prediction and forecasting challenging. The primary aim of this research is to determine which predictive models yield optimal performance in characterizing these complexities and to provide empirical guidance on real-life investment and risk-management applications. Four approaches were used for this forecasting: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), a combination of LSTM-GRU models, and Stochastic Gradient Descent (SGD) regression. The daily historical data were used to train and test each model on different forecast horizons, and performance was measured accordingly by Mean Squared Error (MSE) and Mean Absolute Error (MAE) values. As shown in the results, it can be observed that GRU exhibited the lowest error rates in the majority of the assets, particularly in short-term predictions. LSTM demonstrated a promising ability to capture long dependencies, whereas the hybrid LSTM-GRU system showed a similar performance proficiency by combining the relative superiorities of the two respective models. On the other hand, the conventional SGD regression was the worst among all the deep-learning algorithms, thereby demonstrating the extreme capability of these algorithms in modelling non-linear time sequences. The results confirm GRU as the most viable model for AI-powered crypto prediction and demonstrate the potential of hybrid architecture, at least in certain situations. This study will contribute to the existing debates about the role of deep learning in predicting financial outcomes and provide valuable insights to traders, analysts, and researchers navigating the uncertainties of the digital asset world.

**Keywords:** cryptocurrencies, deep learning, machine learning, volatility.

**JEL Code:** M21, M40.

## Introduction

The world financial system has undergone massive changes due to the rapid development of financial technologies and the proliferation of decentralized digital currencies. The emergence of digital, decentralized assets that run on blockchain-based systems, featuring an extreme price volatility characteristic and a non-linear price market behavior, represents one of the most disruptive innovations in modern finance (Gbadebo, 2023). This decentralized architecture allows secure and cheap cross-border payments, which makes cryptocurrencies an attractive substitute to conventional finance. The cryptocurrency market has grown exponentially in market capitalization and user rates since the dawn of Bitcoin (BTC) in 2009 (Patel et al., 2022; Iqbal et al., 2021). Cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Solana (SOL), Binance Coin, FTX Token and Litecoin (LTC) are a few examples among the thousands of digital assets that exist today (Gbadebo, 2024). The existence of


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these assets has been widely embraced by investors, researchers, traders and policymakers (Nuha et al., 2023).

Digital currencies present unique investment opportunities that have never existed before, while also being subject to increased complexity. Cryptocurrencies, however, do not have any underlying valuation model and are subject to a near infinite number of uncontrollable factors and dynamics- such as social sentiment, geopolitical events, technological solutions and wheeling and dealing- which make their prices highly volatile compared to conventional financial instruments (Iqbal et al., 2021). It is daunting to make accurate predictions about such fluctuations, but the resultant instability has led to an increased level of sophistication and appetite for all data-rich predictive systems that are in a position to navigate in these rough waters (Nuha et al., 2023).

Conventional statistical and machine learning approaches, such as linear regression or support vector machines, have proven incapable of accurately modelling the sequential and non-linear dynamics of financial time series, particularly those as volatile as cryptocurrency prices (Siami-Namini and Namin, 2018). This has drawn increased attention in deep learning models, most notably in recurrent neural networks (RNNs) and their improved versions, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks (Alahmari, 2019). These architectures are perfectly applicable in modelling temporal dependencies and have already proven themselves efficient in various application fields, the most prominent of which are stock forecasting, natural language processing, and time series classification (Gbadebo, 2024).

The objective of this study is to evaluate and compare the performance of four different modeling approaches: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), a combination model that incorporates both LSTM+GRU, and Stochastic Gradient Descent (SGD) regression in predicting the daily closing prices for the top four cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Solana (SOL) from January 1, 2020 to December 31, 2024 using a consistent modeling framework and evaluation criteria ($R^2$ score, Mean Absolute Error [MAE], Root Mean Square Error [RMSE]) to identify which models would produce the most accurate predictions across various market behaviors. The findings of this work not only provide a comparative lens into the strengths and limitations of deep learning and traditional models for crypto forecasting but also offer practical implications for investors, data scientists, and fintech developers who seek to deploy predictive models in real-world trading environments.

## 1. Literature review

Cryptocurrencies have played a major role in shaping the societal and economic environment, and investors have resorted to strategies that can help them make profitable transactions in the face of its volatility. Sentiment analysis by using deep learning algorithms and machine learning combined with the price prediction have been also improved (Hexspoor, 2022). As an example, the DLCFS framework incorporates market sentiment and attributes along with trading volumes in order to promote priced forecasting outcomes of Bitcoin, Ethereum, and Litecoin compared to conventional machine learning algorithms (Gbadebo, 2024).

Because of their dynamic nature, it is difficult to forecast their prices. Litecoin (LTC), Ethereum (ETH), and Bitcoin (BTC) prices have all been predicted using various recurrent neural network (RNN) methods. These algorithms consist of GRU, LSTM, and Bi-LSTM. Compared to the other models, GRU fared better, showing the lowest mean absolute percentage error (MAPE) (Hamayel and Owda, 2021). Another useful technique for forecasting the log-return values of well-known cryptocurrencies is to use the generalized auto-regressive conditional heteroskedasticity (GARCH) and auto-regressive conditional heteroskedasticity (ARCH) models (Bollerslev, 1986).

These models were applied in ARIMA and artificial neural network-based models, where neural networks demonstrated better prediction capacity, along with the closing values of cryptocurrencies (Gbadebo, 2023). Digital currencies, secured by cryptographic hash sets like MD5 and SHA-256, exhibit extreme price volatility, attracting academic interest (Seabe et al., 2023). Deep learning algorithms such as ARIMAX, LSTM, and GRU have been used to predict cryptocurrency prices (Hamayel and Owda, 2021). Considering the interdependencies among different cryptocurrencies, such as predicting Dash prices based on Bitcoin and Litecoin, improves prediction accuracy (Patel et al., 2022). Bitcoin has been the subject of studies aimed at forecasting its market price and stability. Time-series analysis using machine learning techniques, such as ARIMA, FBProphet, and XGBoost, has been employed. ARIMA emerged as the most accurate model for predicting Bitcoin prices, based on metrics such as Mean Absolute Error (MAE), R-squared (R2), and Root Mean Square Error (RMSE) (Gholipour, 2023).

## 2. Methodology

For this research, daily historical closing prices data were collected for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Solana (SOL) from Yahoo Finance from January 1, 2020 to December 31, 2024 (7,308 data points for four cryptocurrencies with substantial market capitalizations) with Date columns and then removed missing values from each dataset. The closing prices were normalized with MinMaxScaler (which scales the values to 0 and 1, a normalization technique that makes neural networks converge faster during training because the higher-value features would not dominate the gradient updates, and gradient updates are more stable). Then convert the time series data to supervised learning format with a sliding window approach and a sequence of 100 days to predict the next day's price (which captures temporal dependencies in the data, which is crucial for models like LSTM and GRU that specialize in sequential learning), divided the resulting dataset into 80% training data and 20% testing data (which preserves the chronological order to reflect a real-world forecasting situation). This same data preprocessing workflow approach is applied to all four cryptocurrencies for a fair comparison of models. Deep learning models, particularly those based on recurrent neural networks, are well-suited for time series forecasting because they can learn both short-term and long-term dependencies in the data (Adekunle et al., 2022; Mahmud et al., 2023; Kim et al., 2021). In this project, we applied three deep learning architectures: LSTM, GRU, and a hybrid LSTM+GRU model.

Long Short-Term Memory Networks, a sophisticated type of recurrent neural network, overcome the shortcomings of traditional RNNs by incorporating memory cells and gating mechanisms, which enable LSTMs to capture short-term and long-term dependencies within sequential data effectively (Alahmari, 2020). This feature is particularly beneficial in the context of financial time series analysis, where trends and temporal patterns play a crucial role in accurate prediction (Zhang et al., 2023). Using two LSTM layers, coupled with dropout regularization, enhanced the model's ability to generalize well and mitigated the risk of overfitting (Zhang et al., 2017).

The Gated Recurrent Unit (GRU) is a simpler alternative to the LSTM for capturing long-term dependencies in sequential data (Dey and Salem, 2017). Although both manage information flow, the GRU achieves this with a more streamlined architecture, using an update and reset gate rather than the LSTM's input, output, and forget gates (Nosouhian et al., 2021). This makes GRUs computationally lighter and enables them to operate at a faster pace, making them particularly advantageous for computationally intensive applications. While LSTMs may have advantages in certain scenarios requiring deep contextual understanding (Chung et al., 2014), GRUs excel at capturing short-term fluctuations and rapid changes (Elsayed et al., 2019), which is critical for analyzing cryptocurrency prices. Although they are generally comparable in performance (Emshagin et al., 2022), GRUs may be preferred because they are more efficient and have simpler hardware implementation (Nosouhian et al., 2021).

This hybrid model combines LSTM and GRU layers to leverage the strengths of each architecture. LSTMs are adept at capturing long-term dependencies, processing the data initially, and extracting relevant historical trends. GRUs, known for quickly adapting to short-term patterns (Low et al., 2023; Sayed et al., 2022), then refine the predictions by focusing on recent fluctuations. This sequential approach aims to improve the model's overall predictive accuracy across various asset types and volatility levels. Emshagin et al. (2022) also discuss hybrid models showing how LSTMs and Gradient Boosting Trees can be combined to achieve superior performance. Stochastic Gradient Descent regression, a type of machine learning and a variant of linear regression, updates the model coefficients iteratively by the negative gradient of the loss function (Singh et al., 2023).

As a type of Machine learning and linear estimator, Stochastic Gradient Descent regression (SGD) is efficient for large datasets by handling individual data points or small subsets, but its capacity to model nonlinear relationships or temporal dependencies is limited (Biswas et al., 2024), which severely hinders its effectiveness in forecasting volatile, non-stationary data like cryptocurrency prices (Dey and Salem, 2017). Therefore, it is essential to explore and develop more advanced models for financial forecasting. Although SGD is computationally efficient, its linear nature and inability to capture complex temporal dynamics, such as trends, seasonality, or sudden shifts in market sentiment, limit its predictive power (Suterman et al., 2024). Flattening input sequences into two-dimensional feature sets further constrained the model in capturing the temporal relationships within the data.

The comparison of deep learning and machine learning in this study highlights the relevance of the selection model for use in financial forecasting problems. GRU and LSTM Deep learning models - massively outclassed SGD and utilized the historical price patterns along with the environmental volatility to enhance their learning to develop a reliable basis of AI-based trading methods and investment strategies. The objective of this study is to enhance the accuracy and efficiency of cryptocurrency price predictions by utilizing deep learning and machine learning models, and to provide valuable insights to investors and researchers.

## 3. Results and discussion

Predicting cryptocurrency prices is a challenging task, but it is crucial for traders and investors who aim to capitalize on market trends. In this section, various machine learning models to predict the price of four popular cryptocurrencies, Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Solana (SOL), will be discussed in detail, and the expected results of the dataset predictions, as well as the evaluation metrics, such as the coefficient of determination ($R^2$ Score), mean absolute error (MAE), and root mean square error (RMSE), for different models are summarized in Tables 1, 2, 3, and 4.

Table 1. **Bitcoin (BTC) price prediction**

| Model | $R^2$ Score | MAE | RMSE |
|---|---|---|---|
| LSTM | 0.9692 | 0.017890 | 0.024335 |
| GRU | 0.9792 | 0.014385 | 0.019993 |
| LSTM+GRU | 0.9446 | 0.027145 | 0.032644 |
| SGD | 0.7282 | 0.055260 | 0.072324 |

*Source:* compiled by the author

Table 1 summarizes the performance of the four models used to forecast Bitcoin prices using historical daily data from 2020 to 2024, evaluated by three standard metrics: $R^2$ Score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Among the deep learning models, the GRU architecture achieved the highest $R^2$ score (0.9792), the lowest MAE (0.0144), and the lowest RMSE (0.0199), indicating that it explained 98% of the variance in BTC price movements and demonstrated the best predictive accuracy and robustness against volatility. The LSTM model also performed well, with an $R^2$ of 0.9692 and similarly low error values. However, the hybrid LSTM+GRU model, which was expected to combine the strengths of both architectures, underperformed slightly, possibly due to overfitting or increased architectural complexity relative to the data. In contrast, the SGD regression model, representing traditional machine learning, had the lowest performance with an $R^2$ score of 0.7282, indicating weaker explanatory power. Its MAE and RMSE were also significantly higher, reinforcing the limitation of linear models in capturing the complex, nonlinear patterns inherent in cryptocurrency time series data. These results demonstrate the superiority of deep learning methods, particularly GRU, for BTC price prediction over the selected time frame.

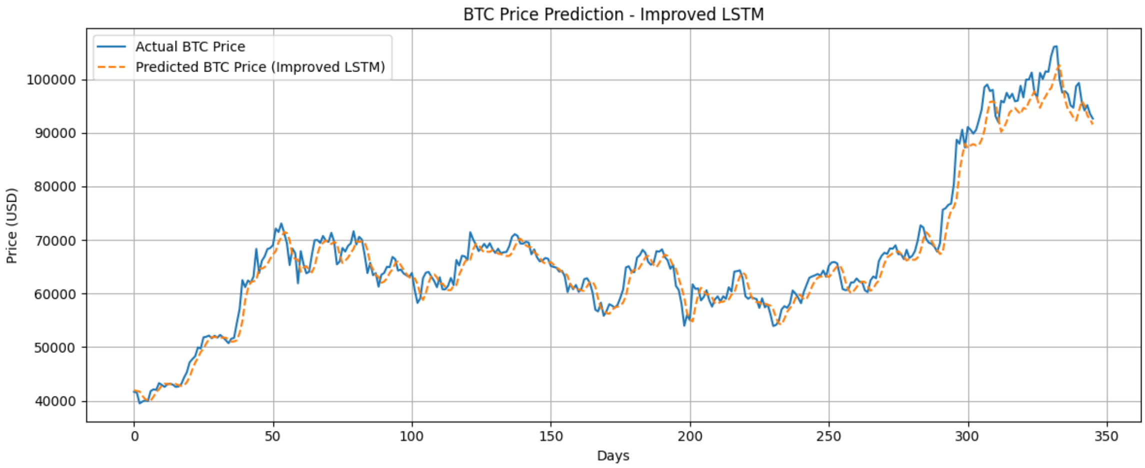


Figure 1. **Actual vs LSTM fitted plot for BTC**
*Source:* compiled by the author

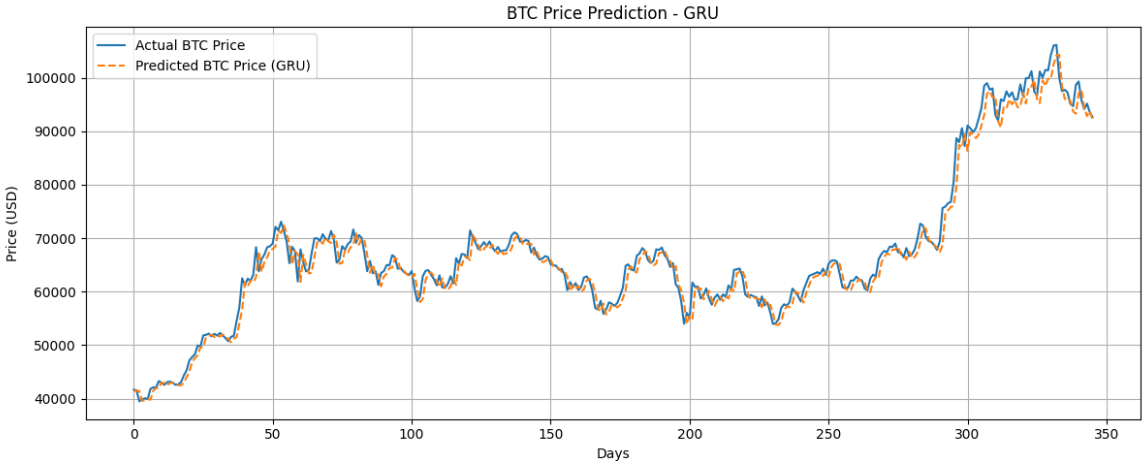


Figure 2. **Actual vs GRU fitted plot for BTC**
*Source:* compiled by the author

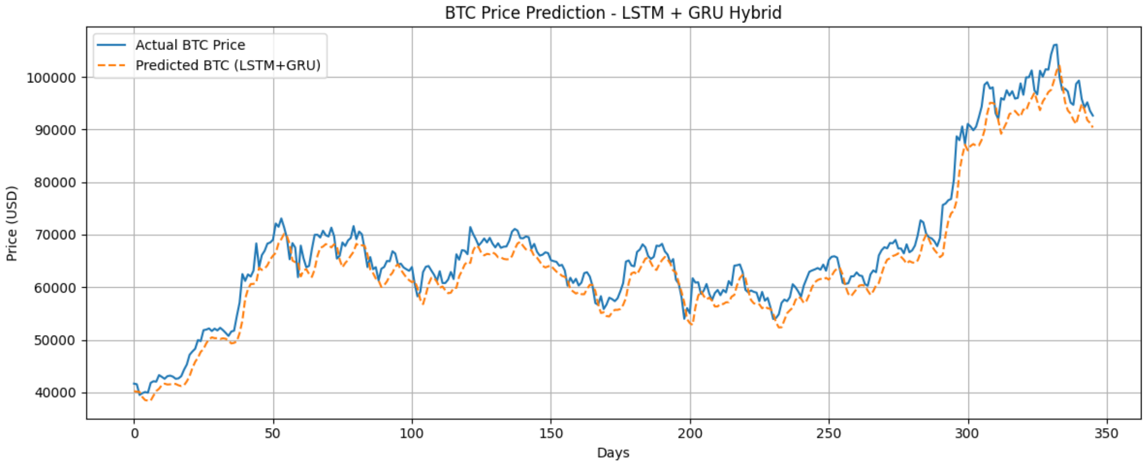


Figure 3. **Actual vs LSTM+GRU fitted plot for BTC**
*Source:* compiled by the author

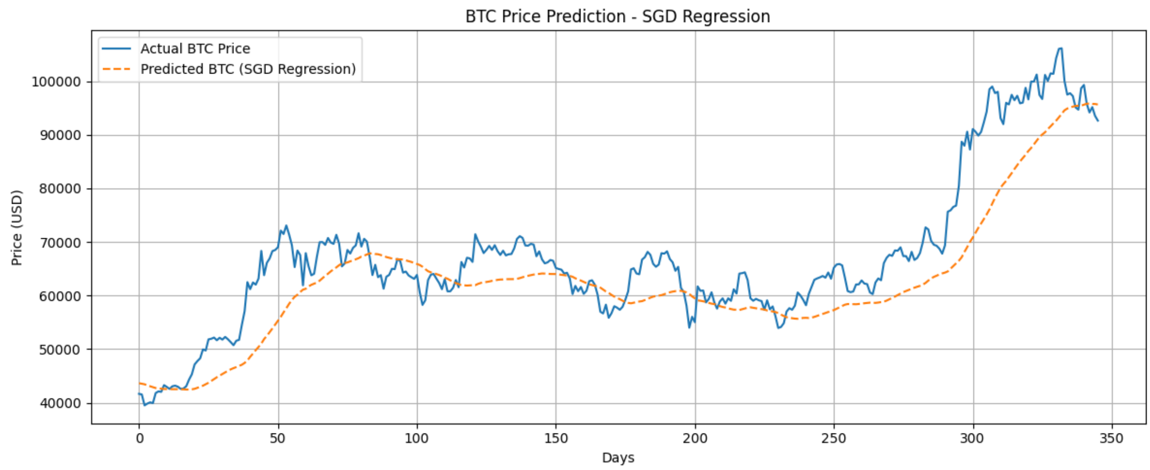


Figure 4. **Actual vs SGD fitted plot for BTC**
*Source:* compiled by author

Additionally, the visual plots (Figures 1-4) of actual versus predicted BTC prices provide intuitive insight into each model's predictive behaviour. The graphs clearly show how well the deep learning models, particularly GRU and LSTM, were able to track the trends and inflexion points of Bitcoin's price movements. The GRU model's predicted line closely follows the actual price curve, with minimal lag and error, even in highly volatile regions. This indicates the model's ability to react rapidly to sudden changes and spikes, which is particularly effective for high-frequency trading decisions, risk analysis, and portfolio rebalancing strategies. Although not as accurate as the LSTM model, it still produces a more gradual and smooth prediction curve, which may be suitable for medium- to long-term forecasting when knowing the overall trends is more significant than being able to track every price movement. On the other hand, the LSTM+GRU hybrid showed greater deviation from the actual price curve, possibly because it is more complex and tends to overfit the training data or underfit the test set. The SGD regression model diverged more significantly from the actual BTC price curve, especially when the price changed rapidly, because its linear structure cannot capture the nonlinear nature of the cryptocurrency behavior. Yet, it can still be used as a simple baseline or as part of an ensemble learning framework. In general, these graphs confirm that deep learning can be successfully applied to predict the price of BTC and also visually confirm that the model may be less confident around price peaks and troughs, which traders, analysts, or researchers can use to look for market timing opportunities, assess model risk, and determine when prediction confidence might wane.

Table 2. **Ethereum (ETH) price prediction**

| Model | $R^2$ Score | MAE | RMSE |
|---|---|---|---|
| LSTM | 0.9296 | 0.021337 | 0.028238 |
| GRU | 0.9391 | 0.020004 | 0.026268 |
| LSTM+GRU | 0.9370 | 0.020258 | 0.026716 |
| SGD | 0.7114 | 0.044995 | 0.057163 |

*Source:* compiled by the author

Table 2 summarizes the predictive performance of the selected models on Ethereum (ETH) price data. As with BTC, the deep learning models clearly outperformed the traditional SGD regression approach across all evaluation metrics. The GRU model achieved the highest $R^2$ score of 0.9391, closely followed by the LSTM+GRU hybrid (0.9370) and the standalone LSTM (0.9296). This suggests that the GRU performed best in capturing the temporal dynamics of ETH price movement. It also had the lowest MAE (0.0200) and lowest RMSE (0.0263), confirming its superior precision and reduced error.

Interestingly, while the LSTM+GRU hybrid model was nearly as accurate, it did not outperform the individual GRU model. This suggests that model stacking may introduce marginal complexity without substantial gains in this case - likely due to overlapping learning patterns between the two recurrent layers. The SGD regression model, on the other hand, delivered the weakest performance with an $R^2$ of 0.7114 and considerably higher MAE and RMSE. This reinforces the limitation of linear models in modelling the non-linear, highly volatile behaviour of cryptocurrency prices.

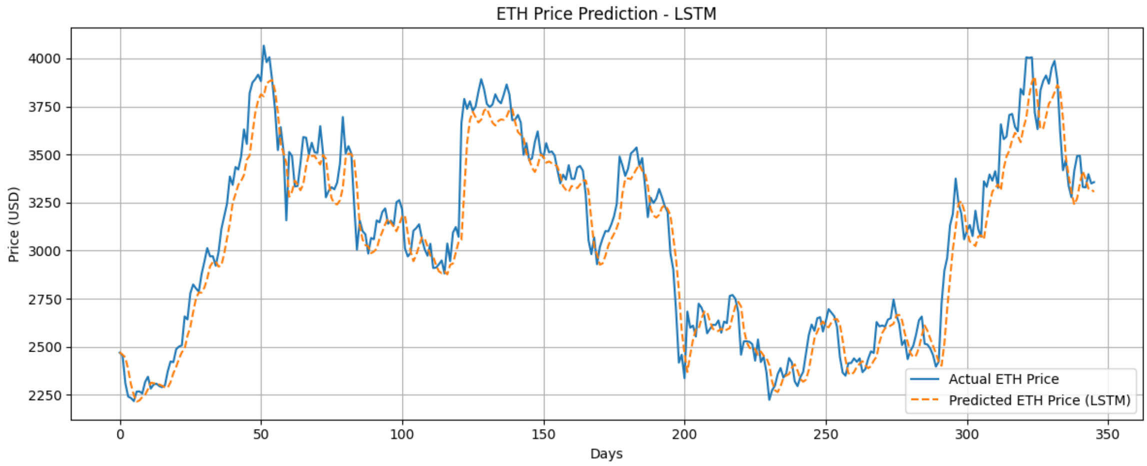


Figure 5. **Actual vs LSTM fitted plot for ETH**
*Source:* compiled by the author

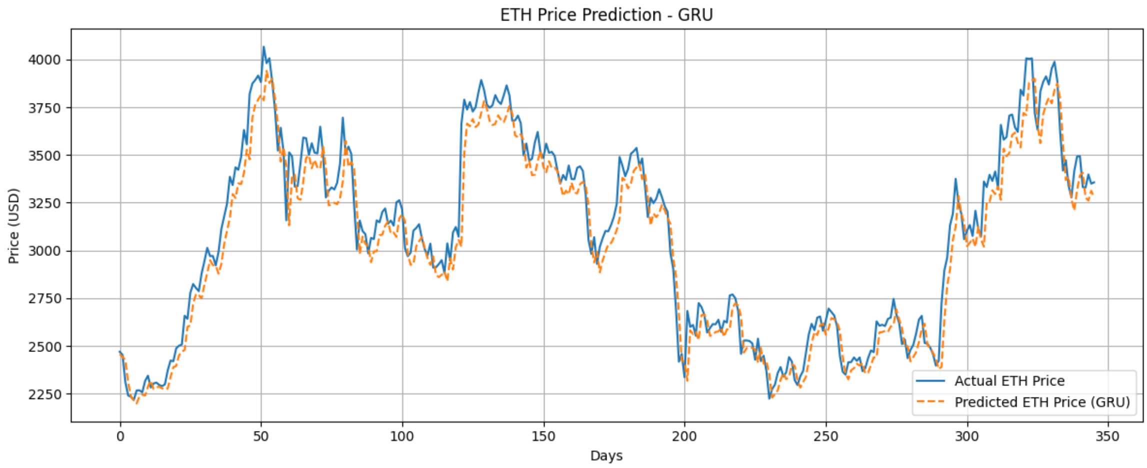


Figure 6. **Actual vs GRU fitted plot for ETH**
*Source:* compiled by the author

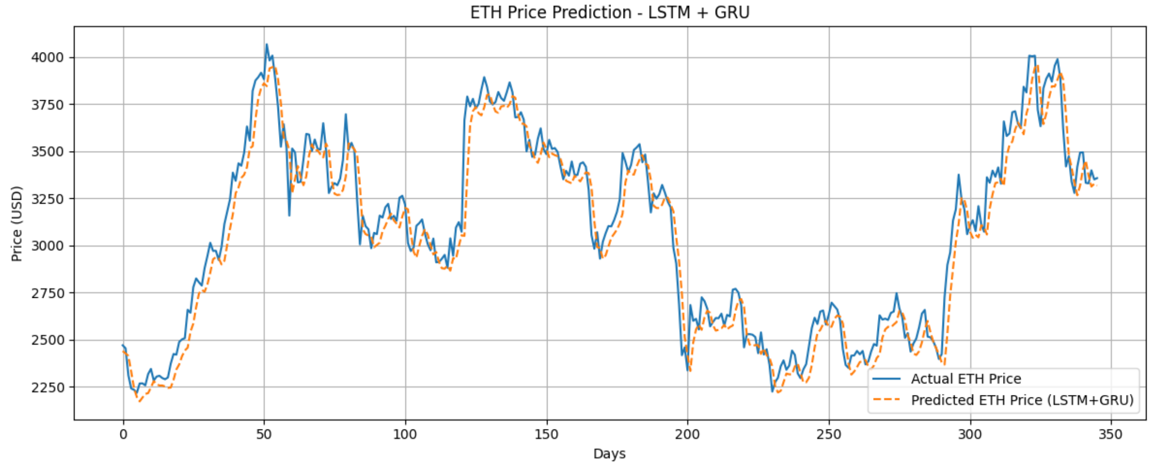


Figure 7. **Actual vs LSTM+GRU fitted plot for ETH**
*Source:* compiled by the author

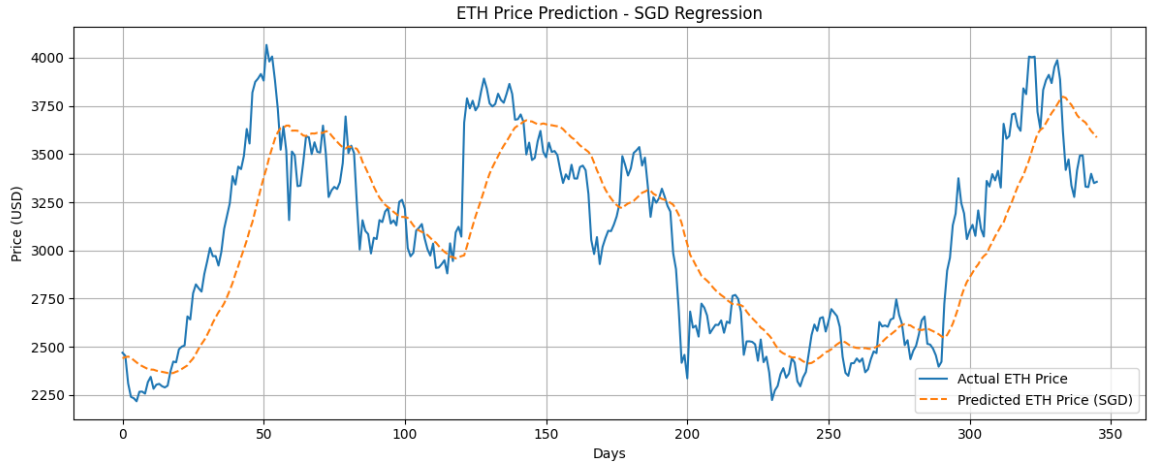


Figure 8. **Actual vs SGD fitted plot for ETH**
*Source:* compiled by the author

The ETH prediction plots (Figures 5-8) provide additional insights. The GRU model's predicted values closely follow the actual price trajectory, including local peaks and valleys, indicating good responsiveness to both trend and volatility. The LSTM and LSTM+GRU also track overall trends well but may lag slightly in fast-moving price shifts. These visualizations can aid in practical investment decision-making by illustrating the consistency of model predictions under different market conditions, helping analysts identify when the model is more or less confident in its forecasts.

The predictive performance of the four models on XRP price data is summarized in Table 3. Consistent with results from BTC and ETH, the deep learning models significantly outperformed the SGD regression model across all evaluation metrics. The LSTM+GRU hybrid model achieved the highest $R^2$ score of 0.9874, indicating that it was able to explain nearly 99% of the variability in XRP price movements. This model also delivered a strong balance of low error values, with an MAE of 0.0121 and an RMSE of 0.0230, confirming its accuracy and robustness. Close behind, the GRU model also performed exceptionally well, slightly outperforming LSTM in terms of MAE and RMSE.

Table 3. **Ripple (XRP) price prediction**

| Model | $R^2$ Score | MAE | RMSE |
|---|---|---|---|
| LSTM | 0.9814 | 0.013255 | 0.027973 |
| GRU | 0.9846 | 0.011294 | 0.025478 |
| LSTM+GRU | 0.9874 | 0.012055 | 0.025478 |
| SGD | 0.7643 | 0.042931 | 0.099635 |

*Source:* compiled by the author

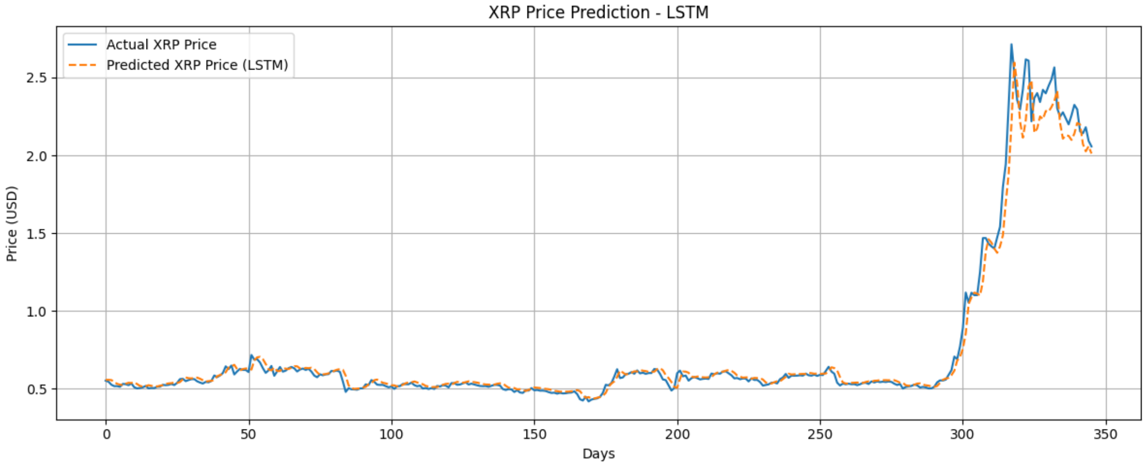


Figure 9. **Actual vs LSTM fitted plot for XRP**
*Source:* compiled by the author

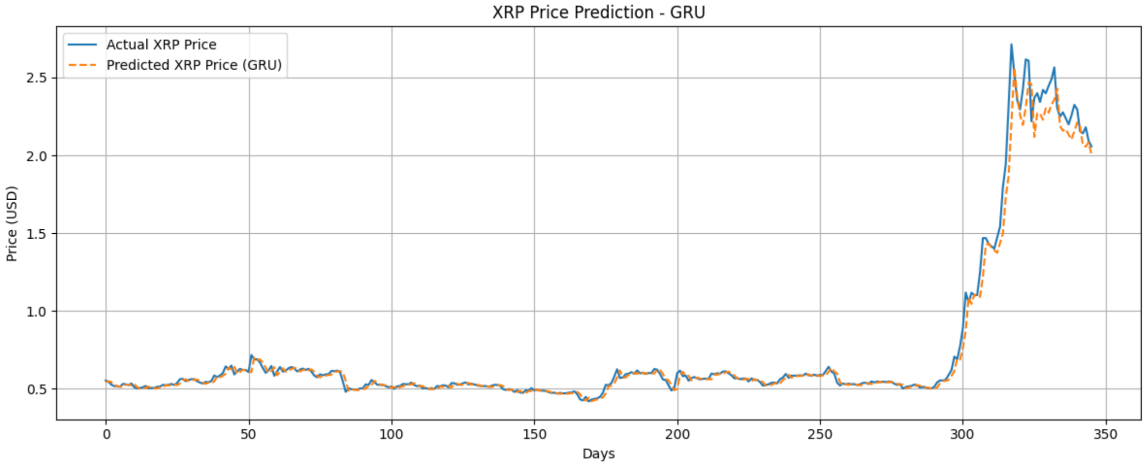


Figure 10. **Actual vs GRU fitted plot for XRP**
*Source:* compiled by the author

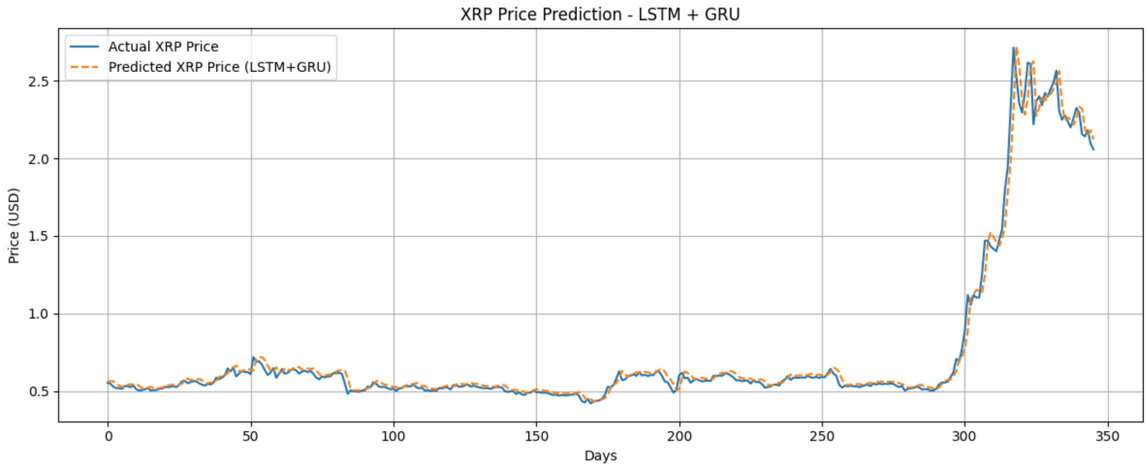


Figure 11. **Actual vs LSTM+GRU fitted plot for XRP**
*Source:* compiled by the author

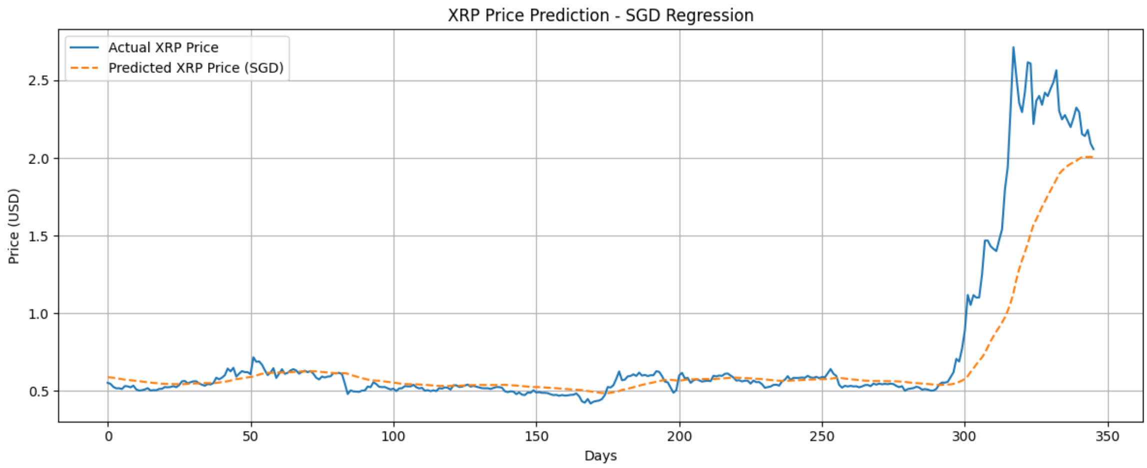


Figure 12. **Actual vs SGD fitted plot for XRP**
*Source:* compiled by the author

The results above demonstrate that GRU architectures are able to efficiently model short- and medium-term temporal dependencies in volatile asset series such as XRP, as evidenced visually in Figure 9-12, where the LSTM+GRU and GRU models track the actual XRP price curve well, both in regions of local fluctuation and long-term trends, and where the hybrid model had slightly smoother and more stable tracking than GRU alone. These results indicate that hybrid deep learning models can be useful for XRP forecasting and can potentially form the basis of automated decision-making tools for traders and analysts.

Table 4. **Solana (SOL) price prediction**

| Model | $R^2$ Score | MAE | RMSE |
|---|---|---|---|
| LSTM | 0.9084 | 0.030459 | 0.038547 |
| GRU | 0.9539 | 0.020727 | 0.027339 |
| LSTM+GRU | 0.9421 | 0.023663 | 0.030655 |
| SGD | 0.6388 | 0.059835 | 0.076758 |

*Source:* compiled by the author

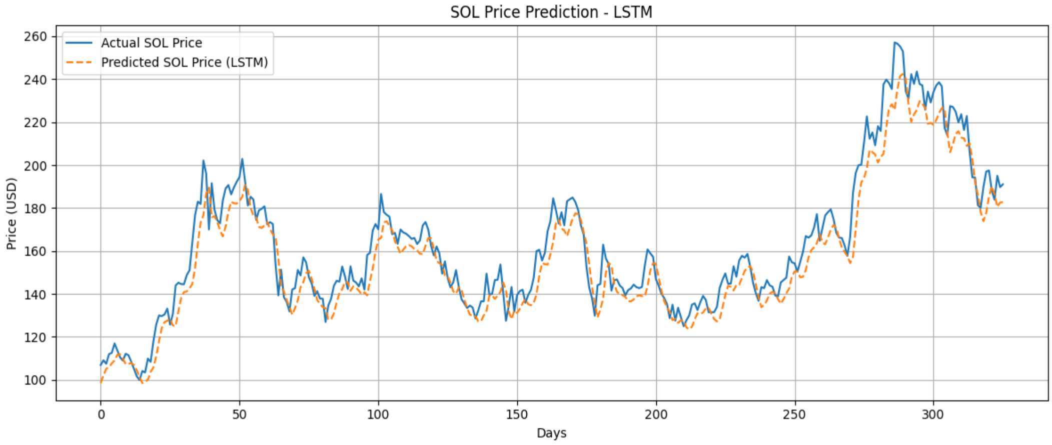


Figure 13. **Actual vs LSTM fitted plot for SOL**
*Source:* compiled by the author

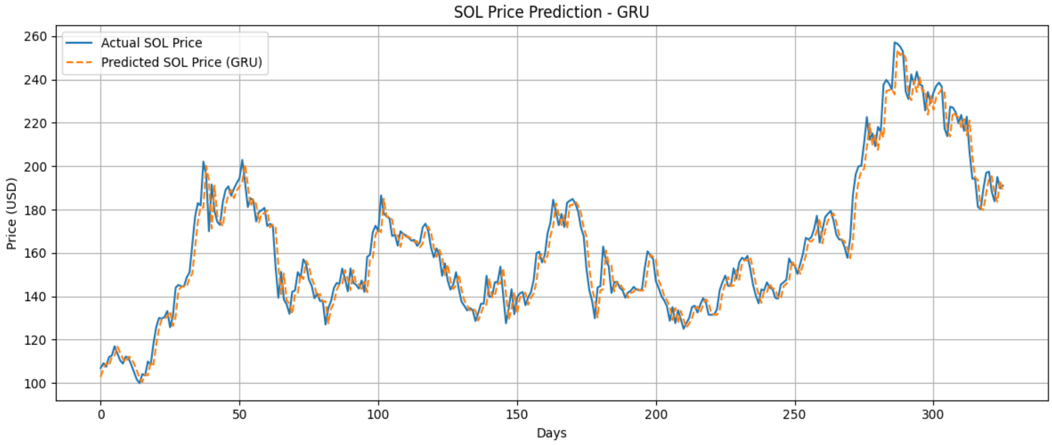


Figure 14. **Actual vs GRU fitted plot for SOL**
*Source:* compiled by the author

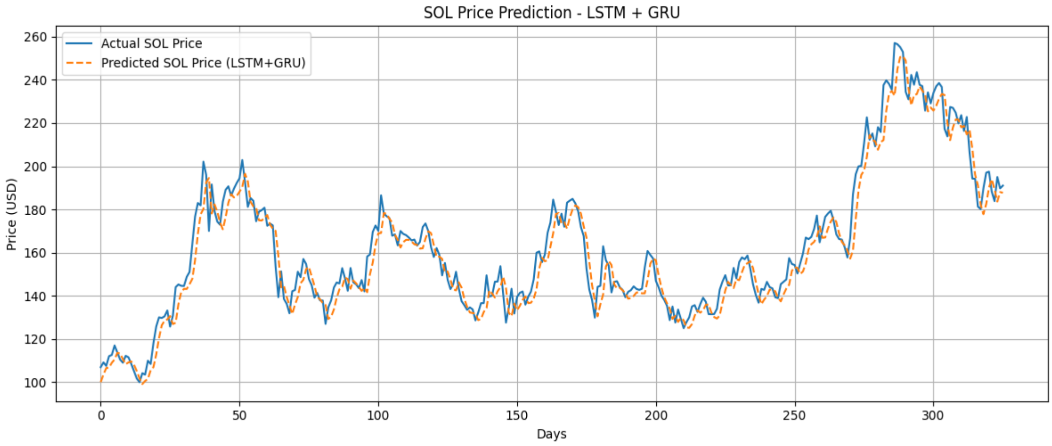


Figure 15. **Actual vs LSTM+GRU fitted plot for SOL**
*Source:* compiled by the author

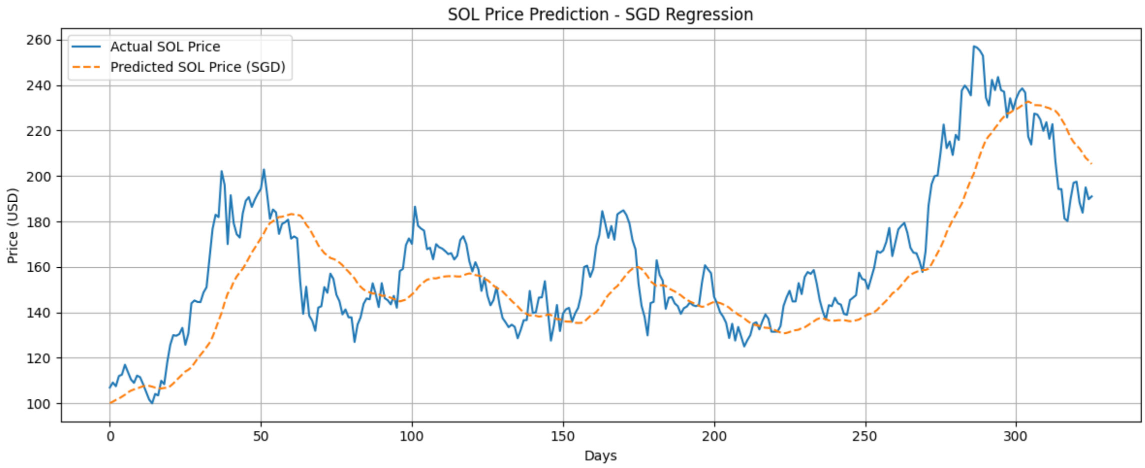


Figure 16. **Actual vs SGD fitted plot for SOL**
*Source:* compiled by the author

Table 4 and Figures 13-16 present the predictive accuracy of the selected models on Solana (SOL) price data. As with the previous cryptocurrencies, the deep learning models significantly outperformed the traditional SGD regression model. GRU had the highest $R^2$ of 0.9539, the lowest MAE (0.0207), and the lowest RMSE (0.0273), indicating that GRU had the most predictive power on SOL price trends and accurately captured the dynamics of SOL's price fluctuations. Interestingly, the LSTM+GRU hybrid did not perform better than GRU, with slightly lower $R^2$ values and higher error rates, indicating that GRU alone was better able to manage sequence complexity in the case of SOL. LSTM performed decently with an $R^2$ of 0.9084, but had slightly higher MAE and RMSE values, which could be due to the relatively high volatility of SOL in certain periods, for which GRU handled the situation better. The prediction lines produced by the deep learning models, particularly GRU, closely followed the actual price movements of SOL, including sharp price increases and decreases, which would give visually trustworthy signals to assist with market timing strategies and short-term forecasting.

**Conclusions**

This research study compared and applied four predictive models —LSTM, GRU, LSTM-GRU, and a supported gradient descent (SGD) regression —to the day-to-day price dynamics of Bitcoin, Ethereum, Ripple, and Solana. The aim was to determine which models best fit the volatility and structural complexity of cryptocurrency markets. Using empirical evidence, it has been demonstrated that, compared to other alternatives, GRU yields better predictive results at all horizons with significantly smaller error bands. LSTM, conversely, has an increased ability to model longer-term dependencies, and the LSTM-GRU composite indicates a more balanced performance representation on all time scales. In comparison, SGD regression produces results with poor performance relative to the other approaches under analysis, revealing the limitations of classic linear regression methods when dealing with the non-stationarity and high dynamics of modern financial sequences.

More than technical accuracy, these findings have practical meaning. Investors and portfolio managers can forecast short-term price movements using GRU-based forecasting models to determine exposure on volatile markets. For researchers, the findings highlight the superiority of the deep learning architecture over more traditional approaches, especially in cases where the asset under consideration has been subjected to irregularities, sudden changes, or continuous fluctuations.

However, the study highlights some significant limitations. None of the models, such as GRU, can accurately quantify abrupt shocks resulting from sudden changes in regulations, major news, or other global economic events. This suggests that predictive models should be incorporated as one of the components of a comprehensive decision-making framework, alongside sentiment analysis, macroeconomic indicators, and continuous retraining approaches, during the decision-making process. Ultimately, the paper demonstrates that deep learning is feasible, and GRU is the most reliable method for predicting the prices of cryptocurrencies. To complement these findings, future work can be conducted to investigate hybrid architectures, combine an extended dataset, and test models under live trading conditions to enhance their applicability in real-world scenarios.

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**Adedeji Daniel Gbadebo:** M.Sc. in Economics and Statistics, University of Benin, Nigeria. Senior Lecturer in Economics at Walter Sisulu University, South Africa. Fields of Scientific Interest: International Trade and Finance; Exchange Rate Dynamics; Monetary Economics. Institutional Address: Department of Accounting Science, Walter Sisulu University, Mthatha Campus, Eastern Cape, South Africa