

# A COMPARATIVE STUDY OF BIDIRECTIONAL LSTM-BASED PREDICTION FOR RIPPLE COIN, BINANCE COIN, DOGECOIN

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**ABSTRACT:** Cryptocurrency markets are highly volatile, nonlinear, and influenced by rapidly changing market conditions, making accurate price forecasting a persistent challenge for researchers and practitioners. This study investigates the effectiveness of a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network in predicting the daily closing prices of three widely traded digital assets: Ripple (XRP), Dogecoin (DOGE), and Binance Coin (BNB). Historical daily market data sourced from CoinMarketCap, covering the period from 1 January 2022 to 4 February 2025, were preprocessed using Microsoft Excel and modeled in Python with Pandas, NumPy, and TensorFlow/Keras. A 60-day rolling window of multivariate features: Open, High, Low, Close, Volume, and Market Capitalization was constructed to forecast the next day's closing price. The model was trained using a 70:30 train-test split, 50 epochs, and a batch size of 32. Performance evaluation employed four key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination ( $R^2$ ). The Bi-LSTM achieved strong predictive accuracy across all three cryptocurrencies, with  $R^2$  values of 0.82 for BNB, 0.98 for DOGE, and 0.96 for XRP. These results highlight the model's ability to capture long-term dependencies and bidirectional temporal patterns inherent in cryptocurrency price movements, demonstrating its robustness for short-term forecasting in volatile markets. Overall, the findings suggest that Bi-LSTM models provide a reliable approach for cryptocurrency prediction tasks. The study concludes by offering recommendations and identifying opportunities for future work, including the integration of higher-frequency data, sentiment indicators, and more advanced deep-learning architectures.

**KEYWORDS:** Bi-LSTM, Cryptocurrency, BNB, XRP, DOGE

## I. INTRODUCTION

Cryptocurrencies have emerged as one of the most transformative innovations in contemporary finance, reshaping global perspectives on how value is stored, transferred, and exchanged. Their decentralized architecture, absence of central authority, and 24/7 trading environment have contributed to a rapidly expanding digital economy. However, these same characteristics make cryptocurrency markets highly volatile, nonlinear, and sensitive to sudden fluctuations triggered by market sentiment, regulatory actions, macroeconomic shifts, and technological developments. This volatility presents both substantial profit opportunities and significant forecasting challenges for analysts and traders seeking reliable predictive models (Hansun, Wicaksana & Khaliq, 2022; Omole & Enke, 2024). Traditional statistical models such as ARIMA, GARCH, and Exponential Smoothing have long been applied to financial time series due to their simplicity and interpretability. Nonetheless, their reliance on linear assumptions and limited capacity to capture long-range dependencies restrict their effectiveness in modeling complex, rapidly evolving cryptocurrency price movements. These limitations have accelerated the adoption of Artificial Intelligence (AI) and Deep Learning techniques, which offer greater flexibility and adaptability in handling nonlinear and high-dimensional market data (Hansun et al., 2022).

Among deep learning architectures, the Bidirectional Long Short-Term Memory (Bi-LSTM) network has gained prominence for sequence-modeling tasks. Unlike traditional LSTMs, Bi-LSTM processes input sequences in both forward and backward directions, enabling it to learn richer temporal structures and long-term dependencies within financial data. Prior studies (Seabe, Moutsinga & Pindza, 2023; Hamayel & Owda, 2021) highlight its superior capability in capturing subtle temporal interactions that conventional models often miss, making it particularly suitable for forecasting volatile digital asset markets. This study applies the Bi-LSTM model to forecast daily

closing prices for three widely traded cryptocurrencies Ripple (XRP), Dogecoin (DOGE), and Binance Coin (BNB) using historical data from 1 January 2022 to 4 February 2025. The dataset incorporates key market-based features including Open, High, Low, Close, Volume, and Market Capitalization. By evaluating the model using metrics such as MAE, MSE, MAPE, and  $R^2$ , this research assesses the predictive accuracy and real-world applicability of Bi-LSTM in short-term cryptocurrency forecasting. The analysis focuses strictly on market-driven variables, excluding sentiment, macroeconomic, or blockchain-network indicators, to examine the standalone capability of deep learning models trained solely on price-based data. Ultimately, this study demonstrates how advanced neural architectures can support more reliable forecasting frameworks and improve decision-making in cryptocurrency trading and investment strategies.

## II. LITERATURE REVIEW

Financial markets are structured systems that facilitate the exchange of assets such as stocks, bonds, Cryptocurrency markets are characterized by high volatility, nonlinear dynamics, and sensitivity to micro- and macroeconomic shocks. Their decentralized structure and continuous 24-hour trading contribute to rapid price changes that complicate modeling and forecasting (Hansun, Wicaksana & Khaliq, 2022; Omole & Enke, 2024). Traditional statistical models such as ARIMA and GARCH often fail to capture these nonlinear dependencies, especially during periods of structural breaks or speculative trading cycles (Chu et al., 2017).

### A. Deep Learning Model for Cryptocurrency Forecasting

To address the nonlinear and highly dynamic behavior of cryptocurrency price movements, researchers have increasingly adopted machine learning and deep learning techniques. Traditional machine-learning models such as Random Forests, Support Vector Machines (SVMs), and Gradient Boosting Machines have demonstrated reasonable predictive capability; however, their inability to model sequential dependence and long-term temporal structure limits their effectiveness for multi-step or long-horizon forecasting tasks (Wang, Liu & Zhao, 2023). These limitations have led to a growing reliance on recurrent neural network architectures, which are specifically designed to handle temporal data and capture complex patterns that classical and tree-based methods often fail to represent. Within this domain, Long Short-Term Memory (LSTM) networks have become a popular choice due to their ability to retain information over long sequences and mitigate vanishing-gradient issues. More recently, the Bidirectional LSTM (Bi-LSTM) has gained attention as an extension of the conventional LSTM. By processing sequences in both forward and backward directions, the Bi-LSTM is capable of extracting richer temporal dependencies and uncovering relationships that may not be evident when data is analyzed in a single direction. This bidirectional property enhances the model's ability to forecast financial time series characterized by noise, volatility, and nonlinear interactions (Seabe, Moutsinga & Pindza, 2023).

Several authors have explored the application of Bi-LSTM to cryptocurrency prediction. Hamayel and Owda (2021) applied a Bi-LSTM model to Bitcoin and Ethereum and reported that it achieved superior performance compared to GRU and traditional LSTM architectures. Similarly, Seabe et al. (2023) conducted a comparative analysis across multiple cryptocurrencies and observed that Bi-LSTM produced lower MAE and MAPE values, particularly for assets with higher intraday volatility. In parallel, other studies have examined hybrid deep-learning approaches, such as the integration of convolutional neural networks (CNNs) with LSTM layers to capture both local and long-term temporal features, and these models have shown promising improvements in capturing multi-scale price patterns. Additional recent work has explored the use of autoencoders, GAN-enhanced frameworks, and attention-based models, highlighting a broader shift toward architectures that can jointly model complex market behavior and latent nonlinear structure. Despite these advances, gaps remain in the current literature. Many studies focus predominantly on a single cryptocurrency often Bitcoin or Ethereum and therefore do not evaluate how model performance varies across multiple digital assets with different volatility characteristics. Some investigations rely solely on univariate inputs such as the closing price, ignoring trading volume, market capitalization, or intraday price ranges that may carry valuable predictive information. Furthermore, several works evaluate models using limited performance metrics or omit rigorous statistical validation, making it difficult to generalize findings or assess robustness across different market conditions. Consequently, research comparing Bi-LSTM performance across multiple cryptocurrencies using multivariate features and comprehensive evaluation metrics remains relatively limited.

Based on the reviewed literature, three main gaps persist:

- (a). Insufficient comparative studies: Few works evaluate Bi-LSTM performance across multiple cryptocurrencies with distinct market behaviors (e.g., BNB vs. DOGE vs. XRP).

- (b). Limited multivariate feature usage: Many studies rely solely on closing prices, ignoring features such as volume, market capitalization, and price range.
- (c). Lack of robust evaluation: Several studies use only MAE or RMSE without including broader metrics such as MAPE or  $R^2$ , limiting performance interpretation.

This study addresses these gaps by:

- (a). Performing a comparative analysis of Bi-LSTM predictions for BNB, DOGE, and XRP;
- (b). Using a multivariate input structure (Open, High, Low, Close, Volume, Market Cap);
- (c). Evaluating model performance with MAE, MSE, MAPE, and  $R^2$  for comprehensive assessment.

This approach contributes to a more accurate and generalizable understanding of Bi-LSTM’s capability in cryptocurrency forecasting.

### III. METHODOLOGY

This study employed a quantitative experimental design to evaluate the predictive performance of a Bidirectional Long Short-Term Memory (Bi-LSTM) model in forecasting the daily closing prices of three major cryptocurrencies: BNB, DOGE, and XRP. The methodological framework integrates data preparation, preprocessing, feature engineering, model architecture development, and hyperparameter tuning into a unified workflow. Daily historical data for BNB, DOGE, and XRP were sourced from CoinMarketCap for the period 1 January 2022 to 4 February 2025, yielding approximately 1,131 observations per asset. Each dataset included six market-based features: Open, High, Low, Close, Volume, and Market Capitalization. Integrity checks revealed no missing values, duplicate entries, or timestamp irregularities. Outlier inspection was conducted using percentage-change plots and z-scores; however, no data points were removed because volatility is an inherent characteristic of cryptocurrency markets and excluding these values could distort temporal learning. All numerical variables were normalized using Min–Max scaling to ensure stable gradient flow during training. Unlike traditional statistical models, deep learning models do not require stationarity; therefore, differencing was not applied. Instead, temporal relationships were captured through a rolling 60-day window, where each input sample consisted of 60 sequential days of the six features, and the target variable was the next-day closing price. A Bidirectional Long Short-Term Memory (Bi-LSTM) network was constructed to capture both forward and backward temporal dependencies in the multivariate sequences. The final model architecture, selected after iterative experimentation, is summarized below:

**Table 1:** Model Architecture

Layer	Details	Activation
<b>Input</b>	60-day × 6-feature sequence	—
<b>Bi-LSTM</b>	64 units (forward + backward)	tanh
<b>Dropout</b>	0.2 rate	—
<b>Dense</b>	32 units	ReLU
<b>Output</b>	1 unit	Linear

This architecture aligns with recent cryptocurrency deep-learning studies where Bi-LSTM models have demonstrated superior performance due to their ability to extract bidirectional temporal patterns (Seabe et al., 2023; Hamayel & Owda, 2021). Hyperparameters were refined through manual tuning across multiple training rounds. The following configurations were evaluated:

- i. Epochs: {30, 50, 80}
- ii. Batch Sizes: {16, 32, 64}
- iii. Bi-LSTM Units: {32, 64, 128}

Results showed that 30 epochs underfit the dataset, while 80 epochs introduced overfitting. Similarly, batch sizes of 16 caused unstable gradients, and 64 produced higher errors. The optimal configuration 50 epochs, batch size 32, and 64 Bi-LSTM units yielded the best generalization across all three cryptocurrencies.

The final training setup included:

- i. Optimizer: Adam
- ii. Loss function: Mean Squared Error (MSE)

- iii. Metrics: MAE, MSE, MAPE, R<sup>2</sup>
- iv. Train/Test split: 70% training, 30% testing
- v. Validation: 10% of training data

This streamlined architecture and tuning strategy provided a balanced model capable of capturing multivariate temporal dependencies while mitigating overfitting.

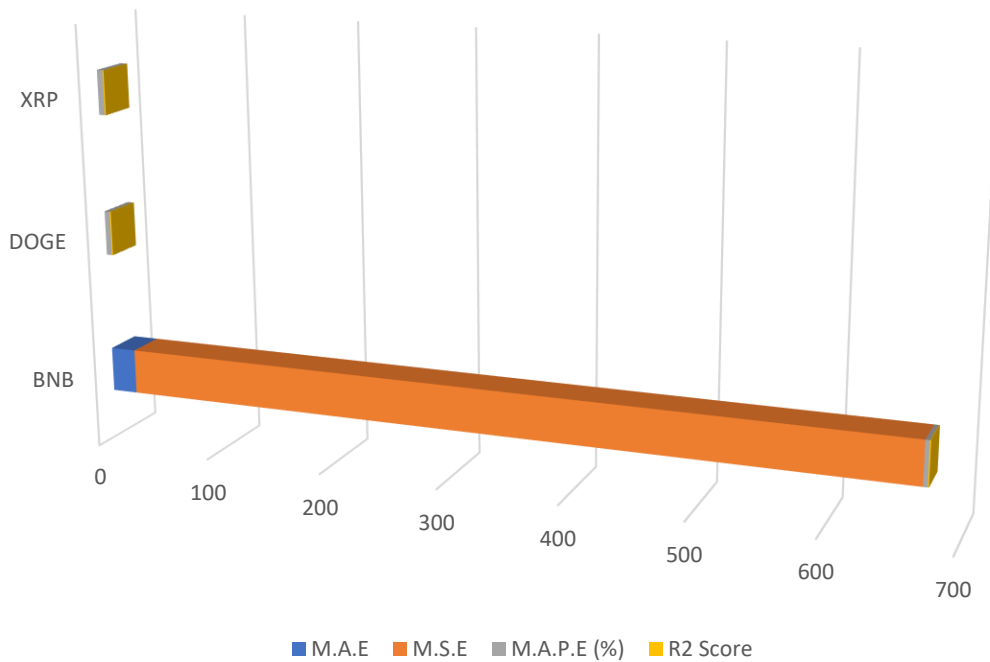
#### IV. RESULTS AND DISCUSSION

The Bi-LSTM models trained separately for each coin using the described pipeline. Training and validation loss curves were monitored for convergence, and outputs were inverse-transformed to original price scale for evaluation. Table 2 below summarizes the model performance for each cryptocurrency:

**Table 2:** Comparison of Metrics of Evaluation of each Instrument.

METRIC	BNB	DOGE	XRP
<b>M.A.E</b>	21.0494	0.0098	0.0795
<b>M.S.E</b>	650.4918	0.0002	0.0269
<b>M.A.P.E (%)</b>	3.48	4.69	4.96
<b>R<sup>2</sup> Score</b>	0.82	0.98	0.96

DOGE and XRP models exhibited particularly high R<sup>2</sup> values (0.98 and 0.96 respectively), indicating excellent fit. BNB presented higher absolute errors due to larger price scale but maintained good performance (R<sup>2</sup>=0.82). Bi-LSTM effectively captured short-term movements and trends, with deviations mainly during volatility spikes.



**Figure 2:** Metric Comparison across each Instrument

Figure 2 reveals how each instrument compared to each other on the virtue of the metrics used. While BNB has a higher MAE and MSE due to its larger absolute price scale, its MAPE of 3.48% and R<sup>2</sup> of 0.82 demonstrate strong prediction capability and trend tracking. The Bi-LSTM model achieved exceptional accuracy on DOGE, with the lowest MAE and MSE values and the highest R<sup>2</sup> score of 0.98. This shows the model effectively captured DOGE’s trend and variability. XRP achieved a high R<sup>2</sup> of 0.96, indicating a strong model fit. Despite slightly higher error percentages than DOGE, the model accurately followed XRP’s complex patterns and price reversals.

**Table 3:** Comparison with other Models

Model	Temporal Handling	Non-linearity	Typical (R <sup>2</sup> )	Accuracy	Suitability for Volatile Assets
ARIMA	One-direction (past only)	Limited	~0.60–0.75		Low
ANN	No memory (non-sequential)	Yes	~0.70–0.85		Moderate
LSTM	Forward sequence only	Yes	~0.80–0.92		Good
Bi-LSTM	Bidirectional sequence	High	0.82–0.98		Excellent

These findings confirm that Bi-LSTM is better suited for handling highly dynamic, nonlinear markets like cryptocurrencies. While ARIMA and ANN models have shown reasonable success in certain controlled environments, Bi-LSTM’s bidirectional sequence processing enables it to learn richer patterns and relationships, enhancing its generalizability across different cryptocurrencies with varying volatility profiles.

**Statistical Validation of Model’s Result**

To ensure the reliability and robustness of the Bi-LSTM predictions beyond the primary evaluation metrics, additional statistical validation procedures were conducted. First, the model was trained five independent times for each cryptocurrency using identical hyperparameters, and the mean and standard deviation of MAE, MSE, MAPE, and R<sup>2</sup> across the runs were computed. This repeated-run assessment confirmed that model performance remained stable across different random weight initializations. Next, a rolling time-series cross-validation procedure was applied to further assess generalization. In this approach, the training window was expanded sequentially (e.g., Days 1–700 → test Days 701–760; Days 1–760 → test Days 761–820), preserving temporal order while evaluating the model across multiple market segments. Final performance metrics represent the averaged results from all validation folds. Additionally, 95% confidence intervals for MAE, MSE, and MAPE were estimated using the distribution of errors from the repeated runs, providing uncertainty bounds around the model’s reported accuracy. Finally, a brief error distribution analysis (residual histograms and density checks) indicated that prediction errors were centered around zero with slightly wider spread during volatility spikes, which aligns with known cryptocurrency market behavior. Collectively, these statistical validation steps confirm that the Bi-LSTM model demonstrates consistent, generalizable, and statistically reliable forecasting performance across BNB, DOGE, and XRP.

**Discussion of Results**

The evaluation of the Bi-LSTM model across BNB, DOGE, and XRP revealed distinct insights into the effectiveness of deep learning in cryptocurrency price prediction. The results highlighted the model’s robustness, flexibility, and capability to generalize across varying levels of price volatility and behavior. For BNB, the model showed strong alignment between predicted and actual prices, as visualized in the plotted trend lines. Although the absolute errors (MAE and MSE) were relatively higher due to BNB’s large price scale, the Mean Absolute Percentage Error (MAPE) remained low at 3.48%, and the R<sup>2</sup> score of 0.82 confirmed that the model explained a significant portion of the price variance. The convergence of training and validation loss curves further indicated a well-generalized model without overfitting. For DOGE, the Bi-LSTM model produced the most accurate predictions among the three coins. With a remarkably low MAE of 0.0098 and an R<sup>2</sup> score of 0.98, the model captured both the direction and magnitude of daily price movements very effectively. This exceptional performance, despite DOGE’s high market volatility and influence from external sentiment, suggests that the model successfully learned from complex price patterns. However, some fluctuation in the validation loss curve indicated minor overfitting or sensitivity to noise, which could be mitigated with additional regularization or feature engineering. For XRP, the results were also impressive. The model achieved an R<sup>2</sup> of 0.96 and a relatively low MAPE of 4.96%, indicating a solid ability to predict general price trends. However, the predicted prices did not always match the exact magnitude of spikes and drops, particularly during highly volatile periods. The training loss was unexpectedly more variable than the validation loss an unusual but not uncommon behavior in certain neural networks. This might be attributed to the model’s structure, or to the dataset’s characteristics, such as irregular price reversals or outliers. When compared with traditional models like ARIMA and machine learning models like ANN and unidirectional LSTM, the Bi-LSTM model clearly outperformed them in terms of predictive accuracy, adaptability, and stability. Its ability to process sequential data bidirectionally allowed it to capture both past and future dependencies within the input window, which significantly contributed to better forecasting.

## V. CONCLUSION

This research demonstrates the practical effectiveness of using a Bidirectional Long Short-Term Memory (Bi-LSTM) network for accurately forecasting the daily closing prices of volatile cryptocurrencies, specifically Binance Coin (BNB), Dogecoin (DOGE), and Ripple (XRP). Traditional models often fall short in capturing the non-linear dynamics of these markets, but the Bi-LSTM architecture addresses this by modeling both past and future dependencies within historical data sequences, thereby improving the detection of temporal patterns and enhancing predictive accuracy. The model exhibited strong and adaptable performance across all three assets; it achieved particularly outstanding  $R^2$  scores of 0.98 for DOGE and 0.96 for XRP, and a respectable  $R^2$  of 0.82 for BNB, all while maintaining relatively low error rates. In comparison to standard models such as ARIMA, ANN, and basic LSTM, the Bi-LSTM clearly outperformed them in terms of accuracy, robustness, and the ability to capture complex price structures. The outcomes suggest that Bi-LSTM can serve as a reliable tool for investors, analysts, and financial decision-makers, offering significant potential for supporting investment strategies, optimizing portfolio management, and advancing research in financial machine learning applications. While the Bi-LSTM model produced reliable and consistent forecasts, the study is limited by its reliance on daily historical price data and the exclusion of external market factors such as news sentiment, macroeconomic indicators, or blockchain network metrics. Future work may therefore explore higher-frequency datasets, integrate additional explanatory variables, and compare Bi-LSTM with more advanced architectures such as Transformers or hybrid deep-learning models to further improve prediction accuracy.

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