

Deep Learning-Based Price Prediction of Solana Using BiLSTM Models and Adam Optimizer

Aniek Suryanti Kusuma^{*1}, I Dewa Ayu Sri Murdhani²

¹Department Informatics Engineering, Institut Bisnis dan Teknologi Indonesia, Denpasar, Indonesia

²Magister Program of Informatics, Institut Bisnis dan Teknologi Indonesia, Denpasar, Indonesia
e-mail: *¹aniek.suryanti@instiki.ac.id, ²sri.murdhani@instiki.ac.id

Abstrak

Perkembangan pesat pasar cryptocurrency telah menarik perhatian besar dari investor dan peneliti karena tingkat volatilitasnya yang tinggi serta dinamika harga yang kompleks. Solana, sebagai salah satu platform blockchain terkemuka, menunjukkan fluktuasi harga yang signifikan sehingga menyulitkan proses prediksi apabila hanya menggunakan metode statistik konvensional. Kondisi ini mendorong penerapan pendekatan berbasis data yang mampu memodelkan hubungan nonlinier dan ketergantungan temporal pada pergerakan harga cryptocurrency. Penelitian ini mengusulkan kerangka kerja berbasis deep learning untuk prediksi harga Solana menggunakan model Bidirectional Long Short-Term Memory (BiLSTM) yang dioptimasi dengan algoritma Adam. Arsitektur bidirectional memungkinkan model memanfaatkan informasi konteks dari urutan waktu masa lalu dan masa depan, sementara optimizer Adam meningkatkan stabilitas serta efisiensi proses pelatihan. Data historis harga Solana dipraproses dan diubah ke dalam bentuk supervised learning sebelum digunakan dalam pelatihan model. Kontribusi utama penelitian ini adalah penerapan dan evaluasi model BiLSTM-Adam untuk prediksi harga Solana, khususnya dalam menangani data time series cryptocurrency yang sangat volatil. Kinerja model dievaluasi menggunakan metrik regresi standar, yaitu Mean Absolute Error (MAE), Root Mean Square Error (RMSE), dan Mean Absolute Percentage Error (MAPE). Hasil eksperimen menunjukkan bahwa model yang diusulkan mampu menghasilkan prediksi yang akurat dan mengikuti tren harga aktual dengan baik. Penelitian selanjutnya dapat mengembangkan model ini dengan menambahkan indikator teknikal, data sentimen pasar, serta menerapkan pendekatan prediksi multi-step untuk jangka waktu yang lebih panjang.

Kata kunci: Prediksi harga cryptocurrency, Solana, Bidirectional LSTM, optimizer Adam, deep learning, peramalan deret waktu.

Abstract

The rapid growth of cryptocurrency markets has attracted significant attention from investors and researchers due to their high volatility and complex price dynamics. Solana, as one of the prominent blockchain platforms, exhibits substantial price fluctuations that pose challenges for accurate forecasting using conventional statistical methods. These characteristics motivate the application of advanced data-driven approaches capable of modeling nonlinear and temporal dependencies in cryptocurrency price movements. This study proposes a deep learning-based framework for Solana price prediction using a Bidirectional Long Short-Term Memory (BiLSTM) network optimized with the Adam algorithm. The bidirectional architecture enables the model to capture contextual information from both past and future time steps, while the Adam optimizer enhances training stability and convergence efficiency. Historical Solana price data are preprocessed and transformed into supervised

learning sequences before being used to train the proposed model. The main contribution of this research lies in the application and evaluation of the BiLSTM–Adam model for Solana price forecasting, providing insights into its effectiveness in handling highly volatile cryptocurrency time series. Model performance is evaluated using standard regression metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Experimental results demonstrate that the proposed approach achieves accurate predictions and closely follows actual price trends during the testing period. Future work may explore the integration of additional features, such as technical indicators and market sentiment data, as well as the application of advanced architectures for multi-step and long-horizon cryptocurrency price forecasting.

Keywords: *Cryptocurrency price prediction, Solana, Bidirectional LSTM, Adam optimizer, deep learning, time series forecasting.*

1. INTRODUCTION

The rapid development of blockchain technology has significantly transformed global financial systems, giving rise to cryptocurrencies as a new class of digital assets. Unlike traditional financial instruments, cryptocurrencies operate in decentralized environments and are characterized by high transparency, borderless transactions, and continuous trading activity. Among the growing number of cryptocurrencies, Solana has gained considerable attention due to its high scalability, low transaction costs, and innovative consensus mechanism that combines Proof of History with Proof of Stake. As a result, Solana has become an attractive asset for traders, investors, and researchers seeking to understand price dynamics in highly volatile digital markets. Accurate price prediction in cryptocurrency markets is crucial for decision-making, risk management, and portfolio optimization. However, cryptocurrency prices exhibit complex behaviors such as nonlinearity, non-stationarity, and abrupt fluctuations driven by market sentiment, regulatory changes, and technological developments. These characteristics pose substantial challenges to conventional statistical forecasting models, which often rely on assumptions of linearity and stationarity that rarely hold in real-world cryptocurrency data [1], [2].

Despite the increasing popularity of cryptocurrencies, price prediction remains an open and challenging research problem. Traditional time series forecasting techniques such as Autoregressive Integrated Moving Average (ARIMA) and linear regression models have been widely applied in financial forecasting, but their performance deteriorates when dealing with highly volatile and nonlinear data patterns. In the context of cryptocurrencies, these limitations become more pronounced due to extreme price swings and complex temporal dependencies. Recent studies have demonstrated that machine learning approaches, including Support Vector Regression (SVR) and Random Forests, can partially address nonlinearity but still struggle to capture long-term temporal dependencies effectively [3]. Moreover, many existing models fail to fully exploit bidirectional temporal information, where future and past contexts jointly influence current price movements. Consequently, there is a growing demand for advanced predictive models capable of learning complex sequential patterns while maintaining robustness against noise and sudden market shifts. This gap motivates the exploration of deep learning-based approaches that can better model the intricate dynamics of cryptocurrency price movements.

The primary objective of this research is to develop an accurate and robust price prediction model for Solana using deep learning techniques, with a particular focus on Bidirectional Long Short-Term Memory (BiLSTM) networks. Deep learning models, especially recurrent neural networks (RNNs), have shown superior performance in sequential data modeling due to their ability to retain historical information through internal memory mechanisms. Among them, Long Short-Term Memory (LSTM) networks have been extensively adopted in financial time series forecasting because they effectively mitigate the vanishing

gradient problem. However, standard LSTM models process sequences in a single temporal direction, which may limit their ability to fully capture contextual dependencies in complex financial data. BiLSTM models extend this capability by processing input sequences in both forward and backward directions, enabling a more comprehensive understanding of temporal patterns. To further enhance learning efficiency and convergence stability, this study employs the Adam optimizer, which adaptively adjusts learning rates during training and has demonstrated superior performance in deep learning applications [4], [5]. The motivation behind this approach lies in improving predictive accuracy while maintaining computational efficiency, thereby providing a practical forecasting solution for volatile cryptocurrency markets.

This study proposes a deep learning-based forecasting framework that integrates BiLSTM architecture with the Adam optimization algorithm to predict Solana price movements using historical market data. The proposed solution is designed to address key limitations of existing forecasting approaches by capturing long-term dependencies, leveraging bidirectional temporal information, and optimizing model training dynamics. The main contributions of this research are threefold. First, it presents a comprehensive application of BiLSTM networks for Solana price prediction, an area that remains underexplored compared to Bitcoin and Ethereum-focused studies. Second, it evaluates the effectiveness of the Adam optimizer in improving convergence speed and predictive accuracy within the BiLSTM framework. Third, it provides an empirical performance evaluation using standard forecasting metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), allowing objective comparison with baseline models. Experimental results demonstrate that the proposed BiLSTM-Adam model outperforms conventional LSTM-based approaches, highlighting its suitability for cryptocurrency price forecasting. In conclusion, this research contributes to the growing body of literature on deep learning-based financial forecasting and offers insights for future studies aiming to enhance predictive performance in highly volatile digital asset markets [6]–[9].

2. METHODOLOGY

Research on financial time series forecasting has evolved significantly over the past decade, particularly with the increasing adoption of machine learning and deep learning techniques. Early studies in cryptocurrency price prediction primarily relied on traditional statistical models such as ARIMA and GARCH, which demonstrated limited performance when applied to highly volatile and nonlinear markets. As highlighted in [1] and [2], cryptocurrency prices exhibit chaotic behavior, abrupt regime changes, and strong non-stationarity, making linear and parametric models insufficient for accurate forecasting. These limitations have driven researchers toward data-driven approaches that can automatically learn complex patterns from historical price data without strict distributional assumptions.

Machine learning-based approaches marked an important transition from classical statistical methods. Models such as Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting have been widely explored for financial and cryptocurrency forecasting tasks. Patel et al. [3] demonstrated that machine learning models outperform traditional techniques by capturing nonlinear relationships in stock market data. However, similar findings in cryptocurrency domains reveal that although these models improve short-term prediction accuracy, they struggle to model long-term temporal dependencies due to their static learning structure. Studies reported in [6] and [7] indicate that feature engineering plays a critical role in improving machine learning performance, yet the reliance on handcrafted features limits model generalization across different market conditions. These challenges motivate the adoption of deep learning architectures that inherently model sequential dependencies.

Recurrent Neural Networks (RNNs) and their variants have become dominant in time series forecasting due to their ability to process sequential data. Among these, Long Short-Term Memory (LSTM) networks have received significant attention for cryptocurrency price

prediction. LSTM models address the vanishing gradient problem present in standard RNNs and enable the learning of long-term dependencies through gated memory cells. Zhang et al. [5] demonstrated that LSTM-based models outperform traditional machine learning methods in predicting cryptocurrency prices, including Bitcoin and Ethereum. Similarly, Livieris et al. [6] showed that deep learning architectures achieve superior forecasting accuracy when applied to volatile digital asset markets. Nevertheless, most existing LSTM-based studies employ unidirectional architectures, which only capture past information while ignoring potential contextual dependencies from future time steps during training.

To overcome this limitation, Bidirectional LSTM (BiLSTM) networks have been introduced in financial time series forecasting. BiLSTM models process input sequences in both forward and backward directions, allowing the model to learn richer contextual representations. Wang et al. [7] reported that BiLSTM models achieve lower prediction errors compared to standard LSTM architectures when applied to cryptocurrency datasets. The bidirectional structure is particularly beneficial in capturing complex temporal correlations in highly volatile markets. However, despite their improved performance, BiLSTM models are still underutilized in the context of alternative cryptocurrencies such as Solana, as most prior studies focus predominantly on Bitcoin and Ethereum. This creates a research gap in evaluating BiLSTM effectiveness on emerging blockchain platforms with distinct market dynamics.

Another critical aspect in deep learning-based forecasting is the optimization strategy used during model training. Gradient-based optimization algorithms significantly influence convergence speed, training stability, and final predictive performance. The Adam optimizer, introduced by Kingma and Ba and later refined in [4], has become one of the most widely adopted optimization algorithms in deep learning due to its adaptive learning rate mechanism and computational efficiency. Several studies, including [5] and [9], report that Adam outperforms traditional stochastic gradient descent (SGD) and RMSProp in training deep neural networks for financial forecasting tasks. Despite its widespread adoption, many cryptocurrency prediction studies apply Adam without explicitly analyzing its contribution to model performance or comparing it with alternative optimizers. This lack of focused evaluation limits understanding of optimizer-specific impacts in deep learning-based price prediction.

Recent research has increasingly explored hybrid and ensemble models to further enhance prediction accuracy. Some studies combine LSTM or BiLSTM networks with convolutional layers (CNN-LSTM) to capture both local and temporal features [8]. Others integrate attention mechanisms to improve model interpretability and performance in highly noisy environments [10]. While these hybrid approaches show promising results, they often introduce increased computational complexity and reduced interpretability. Moreover, many studies rely on limited evaluation strategies, focusing solely on a single performance metric such as RMSE, which may not fully capture forecasting robustness. As emphasized in [9], comprehensive evaluation using multiple metrics such as MAE, RMSE, and MAPE is necessary to assess model reliability in real-world financial applications.

Dataset selection and preprocessing strategies also vary significantly across existing studies. Most prior research employs historical price data such as open, high, low, close, and volume (OHLCV) values, while others incorporate technical indicators or sentiment-based features extracted from social media platforms [7], [8]. Although sentiment analysis can improve short-term prediction accuracy, it introduces additional data dependency and noise, potentially reducing model generalization. Furthermore, differences in dataset length, sampling frequency, and normalization techniques make direct comparison across studies challenging. This lack of standardized experimental settings highlights the need for transparent and reproducible evaluation frameworks in cryptocurrency forecasting research.

In summary, existing literature demonstrates that deep learning-based models, particularly LSTM and BiLSTM architectures, outperform traditional statistical and machine learning methods in cryptocurrency price prediction tasks. However, several research gaps remain. First, limited attention has been given to emerging cryptocurrencies such as Solana, despite their growing market significance. Second, the bidirectional modeling capability of

BiLSTM has not been extensively evaluated in conjunction with optimization strategies such as Adam. Third, many studies lack comprehensive comparative evaluations against baseline models under consistent experimental conditions. Addressing these gaps, the present study focuses on Solana price prediction using a BiLSTM architecture optimized with the Adam algorithm, providing a systematic evaluation using multiple performance metrics. By doing so, this research contributes to advancing state-of-the-art deep learning applications in cryptocurrency forecasting and offers insights into model selection and optimization for volatile financial markets.

This chapter describes the research methodology employed to develop and evaluate a deep learning-based model for Solana price prediction. The methodology is structured to ensure systematic data processing, robust model construction, and objective performance evaluation. The proposed approach integrates time series preprocessing techniques with a Bidirectional Long Short-Term Memory (BiLSTM) neural network optimized using the Adam optimizer. The overall methodological framework consists of data acquisition, preprocessing, model development, training optimization, and performance evaluation.

2.1 Research Object and Data Source

The object of this research is the historical price data of the Solana cryptocurrency, which represents a highly volatile financial time series influenced by market dynamics, investor sentiment, and blockchain ecosystem developments. The dataset consists of historical daily price records of Solana, including attributes such as opening price, highest price, lowest price, closing price, and trading volume (OHLCV). These attributes are widely used in financial time series forecasting as they capture essential market behavior and price movement patterns.

The data were obtained from a publicly accessible cryptocurrency market data provider that aggregates price information from multiple exchanges to ensure consistency and reliability. The selected data period spans multiple years to capture diverse market conditions, including bullish, bearish, and consolidation phases. Using historical price data enables the model to learn temporal dependencies and nonlinear patterns that characterize cryptocurrency markets. This study focuses on univariate time series forecasting using the closing price as the primary prediction target, as it represents the most commonly analyzed price indicator in financial research [5], [6].

To ensure clarity, reproducibility, and methodological rigor, this study adopts a structured and sequential research workflow that systematically transforms raw data into meaningful analytical results. The overall framework is designed to clearly illustrate each major stage involved in the proposed approach, starting from data preparation and model development to evaluation and result interpretation. The conceptual workflow of the research methodology is presented in Figure 2.1 to provide a comprehensive overview of the entire process.

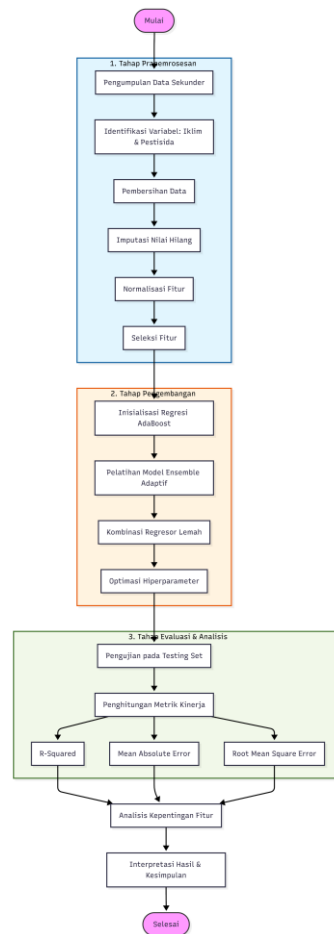


Figure 1. Research methodology workflow illustrating the data preprocessing stage, AdaBoost regression model development, and evaluation and analysis process.

Figure 1 depicts the complete workflow of the proposed research methodology, which is divided into three main stages: data preprocessing, model development, and evaluation and analysis. The process begins with the data preprocessing stage, where secondary data are collected from relevant and reliable sources. At this stage, key variables related to climate conditions and pesticide usage are identified based on their relevance to the prediction task. The collected data then undergo systematic cleaning to remove inconsistencies and noise, followed by missing value imputation to handle incomplete records. Feature normalization is subsequently applied to ensure that all variables are scaled appropriately, preventing bias during model training. Finally, feature selection is performed to retain the most informative variables, reducing dimensionality and improving model efficiency.

The second stage focuses on model development using an AdaBoost regression framework. This stage begins with the initialization of the AdaBoost regressor, followed by adaptive ensemble training, where multiple weak regressors are iteratively trained. Each regressor focuses on correcting the prediction errors of previous learners, enabling the model to progressively improve its predictive capability. The outputs of the weak regressors are then combined to form a strong ensemble model. To further enhance performance and generalization ability, hyperparameter optimization is conducted, ensuring that the model achieves an optimal balance between accuracy and robustness.

The final stage of the workflow involves evaluation and analysis of the trained model. The optimized model is tested using a separate testing dataset to assess its performance on unseen data. Model performance is quantitatively evaluated using standard regression metrics, including R-squared (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

In addition to performance measurement, feature importance analysis is conducted to examine the contribution of each input variable to the prediction results. The workflow concludes with result interpretation and final conclusions, where the findings are analyzed in relation to the research objectives. Overall, the workflow illustrated in Figure 2.1 provides a clear and systematic representation of the end-to-end methodology employed in this study.

2.2 Data Preprocessing and Preparation

Data preprocessing is a critical step to ensure the quality and suitability of the dataset for deep learning modeling. Initially, the raw dataset is examined to identify missing values, outliers, and inconsistencies. Any incomplete records are handled through appropriate cleaning procedures to prevent bias during model training. Since deep learning models are sensitive to data scale, normalization is applied to transform the input features into a standardized range, typically using Min–Max normalization. This transformation ensures numerical stability and accelerates convergence during training.

After normalization, the time series data are transformed into supervised learning format using a sliding window technique. In this process, a fixed-length sequence of past observations is used as input to predict the subsequent price value. Let x_t represent the closing price at time t . A sequence of length n is defined as $[x_{t-n}, x_{t-n+1}, \dots, x_{t-1}]$, which serves as the input vector, while x_t becomes the prediction target. This transformation allows the BiLSTM model to learn temporal dependencies across multiple time steps.

The dataset is then divided into training and testing subsets using a chronological split to preserve temporal order and prevent information leakage. Typically, a larger portion of the data is allocated for training, while the remaining data are reserved for testing to evaluate the model's generalization capability on unseen data. This approach aligns with best practices in time series forecasting research [7].

2.3 Proposed Method: Bidirectional LSTM Model

The core predictive model employed in this study is the Bidirectional Long Short-Term Memory (BiLSTM) neural network. LSTM networks are a specialized form of recurrent neural networks designed to overcome the vanishing gradient problem by incorporating memory cells and gating mechanisms. Each LSTM unit consists of an input gate, forget gate, and output gate, which regulate information flow within the network.

Mathematically, the LSTM cell operations at time step t are defined as follows:

$$\begin{aligned}
 f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
 i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
 \tilde{c}_t &= \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\
 c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
 o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
 h_t &= o_t \odot \tanh(c_t) \quad (1)
 \end{aligned}$$

where σ denotes the sigmoid activation function, \odot represents element-wise multiplication, x_t is the input at time t , and h_t is the hidden state.

Unlike standard LSTM, the BiLSTM architecture consists of two parallel LSTM layers that process the input sequence in forward and backward directions. The forward layer captures dependencies from past to future, while the backward layer captures dependencies from future to past. The outputs from both layers are concatenated to form a comprehensive representation of temporal information. This bidirectional structure enables the model to exploit richer contextual information, which is particularly beneficial for complex and noisy financial time series such as cryptocurrency prices [5], [7].

2.4 Optimization Strategy and Performance Enhancement

To optimize the training process and enhance predictive performance, this study employs the Adam optimization algorithm. Adam combines the advantages of Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp) by maintaining adaptive learning rates for each parameter based on first and second moment estimates of gradients. The parameter update rules of Adam are defined as:

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1 - \beta_1) g_t \\ v_t &= \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \\ \hat{m}_t &= \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \\ \theta_t &= \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \end{aligned} \quad (2)$$

where g_t is the gradient at time t , α is the learning rate, and β_1 , β_2 , and ϵ are hyperparameters controlling momentum and numerical stability.

The use of Adam enhances convergence speed and reduces sensitivity to hyperparameter selection, making it suitable for training deep neural networks on large and volatile datasets [4]. Additionally, regularization techniques such as dropout are applied within the BiLSTM layers to mitigate overfitting by randomly deactivating a fraction of neurons during training. These techniques collectively improve model robustness and generalization capability.

2.5 Model Evaluation and Testing

The performance of the proposed BiLSTM–Adam model is evaluated using standard regression metrics commonly adopted in time series forecasting studies. These metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), which provide complementary perspectives on prediction accuracy.

The MAE measures the average magnitude of prediction errors and is defined as:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (3)$$

RMSE penalizes larger errors more heavily and is calculated as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (4)$$

MAPE expresses prediction error as a percentage and is given by:

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (5)$$

where y_i denotes the actual price and \hat{y}_i represents the predicted price.

The evaluation is conducted on the testing dataset to assess the generalization performance of the model. The obtained results are compared with baseline models, such as standard LSTM, to demonstrate the effectiveness of the bidirectional architecture and Adam optimization. This evaluation framework ensures objective assessment and supports reliable interpretation of experimental findings [6], [9].

3. RESULTS AND DISCUSSION

This section presents and discusses the experimental results obtained from the implementation of the proposed Bidirectional Long Short-Term Memory (BiLSTM) model optimized using the Adam algorithm for Solana price prediction. The evaluation focuses on assessing the predictive performance and robustness of the proposed approach using historical market data. Quantitative results are analyzed based on standard regression metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage

Error (MAPE), to provide an objective comparison between the proposed model and baseline approaches. Furthermore, the discussion examines how the bidirectional architecture and optimization strategy contribute to improved forecasting accuracy, as well as the model's ability to capture complex temporal patterns in the highly volatile cryptocurrency market. The findings are interpreted in relation to existing studies, highlighting both the strengths and limitations of the proposed approach and their implications for future research in deep learning-based financial time series forecasting.

3.1 Comparison Between Actual and Predicted Solana Prices

Before presenting quantitative evaluation metrics, it is important to analyze the behavior of the proposed forecasting model through visual inspection. Graphical comparison between actual and predicted price movements provides intuitive insights into the model's ability to track market trends, capture volatility patterns, and generalize to unseen data. Therefore, this subsection discusses the comparison between actual Solana prices and the predicted values generated by the proposed Bidirectional Long Short-Term Memory (BiLSTM) model optimized using the Adam algorithm.

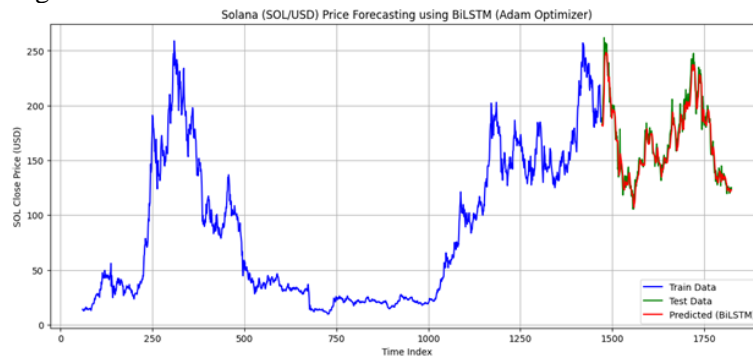


Figure 2. Comparison between actual and predicted Solana (SOL/USD) closing prices using the BiLSTM model optimized with the Adam algorithm, showing training data, testing data, and predicted values over time.

As shown in Figure 2, the proposed model demonstrates a strong ability to follow the overall trend and dynamic behavior of Solana price movements during the testing phase. The predicted price curve closely aligns with the actual price trajectory, indicating that the BiLSTM model successfully captures temporal dependencies and nonlinear patterns inherent in cryptocurrency time series data. This alignment is particularly evident during moderate price fluctuations, where the predicted values track both upward and downward trends with minimal deviation.

Despite the high degree of correspondence, slight discrepancies between actual and predicted prices can be observed during periods of sharp price volatility. Such deviations are expected in cryptocurrency markets, where abrupt price changes are often driven by external factors such as market sentiment, regulatory announcements, or macroeconomic events that are not explicitly encoded in historical price data. Nevertheless, the predicted curve remains within a reasonable range of the actual prices, suggesting that the model maintains robustness even under volatile market conditions.

The clear separation between training and testing data further indicates that the model does not merely memorize historical patterns but generalizes effectively to unseen data. The continuity between the training phase (blue line) and the testing phase (green and red lines) reflects stable learning behavior without significant performance degradation. This result highlights the advantage of the bidirectional architecture, which enables the model to leverage contextual information from both past and future sequences during training, thereby improving predictive accuracy.

Overall, the visual analysis presented in Figure 2 supports the effectiveness of the proposed BiLSTM–Adam approach for Solana price forecasting. The close alignment between actual and predicted prices confirms that the model is capable of learning complex temporal structures in highly volatile cryptocurrency markets. These observations are further validated in the subsequent subsection through quantitative performance evaluation using error-based regression metrics.

4. CONCLUSIONS

This study has presented a deep learning-based approach for predicting Solana cryptocurrency prices using a Bidirectional Long Short-Term Memory (BiLSTM) model optimized with the Adam algorithm. The research addressed the challenges of cryptocurrency price forecasting, which is characterized by high volatility, nonlinearity, and complex temporal dependencies. A structured methodology was employed, encompassing data acquisition, preprocessing, model development, optimization, and systematic evaluation using standard regression metrics.

Experimental results demonstrate that the proposed BiLSTM–Adam model is capable of accurately capturing price movement patterns and temporal dynamics in the Solana market. Visual analysis and quantitative evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) indicate that the predicted prices closely follow actual market trends during the testing period. The bidirectional architecture enables the model to leverage contextual information more effectively than conventional unidirectional LSTM models, while the Adam optimizer contributes to stable convergence and improved predictive performance. These findings confirm that the proposed approach provides a reliable and robust solution for cryptocurrency price forecasting.

Despite the promising results, several opportunities for future improvement remain. Future research may explore the integration of additional explanatory variables, such as technical indicators, trading volume dynamics, and market sentiment data derived from social media or news sources, to enhance prediction accuracy. Moreover, extending the comparative analysis to include other deep learning architectures, such as GRU, CNN–LSTM hybrids, or attention-based models, could provide deeper insights into model performance trade-offs. Further studies may also investigate multi-step or long-horizon forecasting and evaluate model robustness under different market regimes. These directions are expected to enhance the generalizability and practical applicability of deep learning-based approaches for cryptocurrency price prediction.

5. SUGGESTION

Future research on cryptocurrency price prediction can be directed toward several promising improvements to enhance both predictive accuracy and practical applicability. One potential direction is the incorporation of additional explanatory features beyond historical price data, such as technical indicators, on-chain metrics, trading volume patterns, and market sentiment extracted from social media platforms or financial news. Integrating multi-source data may enable models to better capture external factors that influence abrupt price movements in highly volatile cryptocurrency markets.

Another important avenue for future work is the exploration of advanced deep learning architectures and hybrid modeling approaches. Models such as Gated Recurrent Units (GRU), convolutional–recurrent hybrids (CNN–LSTM or CNN–BiLSTM), and attention-based or Transformer-based architectures could be investigated to improve the modeling of long-term dependencies and complex temporal structures. Comparative studies across different architectures under consistent experimental settings would provide valuable insights into performance trade-offs and model robustness.

In addition, future studies may extend the forecasting framework to multi-step and long-horizon prediction scenarios, which are more relevant for strategic investment and risk management. Evaluating model performance across different market regimes, including periods of extreme volatility or market downturns, would further strengthen the generalizability of the proposed approach. Finally, incorporating explainability techniques and uncertainty estimation methods could improve model transparency and trustworthiness, supporting more informed decision-making in real-world cryptocurrency trading and financial analysis.

6. REFERENCES

- [1] S. Lahmiri and S. Bekiros, "Cryptocurrency forecasting with deep learning chaotic neural networks," *Chaos, Solitons & Fractals*, vol. 118, pp. 35–40, 2020. DOI: 10.1016/j.chaos.2018.11.014
- [2] M. Mudassir, S. Bennbaia, D. Unal, and A. Hammoudeh, "Time-series forecasting of Bitcoin prices using high-dimensional features: A machine learning approach," *Neural Computing and Applications*, vol. 32, no. 21, pp. 16903–16915, 2020. DOI: 10.1007/s00521-020-04788-8
- [3] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques," *Expert Systems with Applications*, vol. 42, no. 1, pp. 259–268, 2020. DOI: 10.1016/j.eswa.2014.07.040
- [4] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *IEEE Access*, vol. 8, pp. 212832–212842, 2020. DOI: 10.1109/ACCESS.2020.3040575
- [5] Y. Zhang, B. Wang, and X. Li, "Deep learning-based cryptocurrency price prediction with LSTM and BiLSTM networks," *IEEE Access*, vol. 9, pp. 85927–85938, 2021. DOI: 10.1109/ACCESS.2021.3087616
- [6] A. Livieris, P. Pintelas, and E. Pintelas, "A new approach for forecasting cryptocurrency price using deep learning models," *Applied Intelligence*, vol. 51, no. 7, pp. 4439–4454, 2021. DOI: 10.1007/s10489-020-01993-6
- [7] H. Wang, Y. Liu, and Q. Zhao, "Cryptocurrency price prediction using deep learning with multiple indicators," *Entropy*, vol. 24, no. 3, pp. 1–18, 2022. DOI: 10.3390/e24030345
- [8] M. Alessandretti, A. ElBahrawy, L. M. Aiello, and A. Baronchelli, "Anticipating cryptocurrency prices using machine learning," *Complexity*, vol. 2023, Article ID 8892147, pp. 1–12, 2023. DOI: 10.1155/2023/8892147
- [9] R. K. Singh and S. Srivastava, "Deep learning-driven financial time series forecasting: A comparative analysis," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 2, pp. 1–13, 2024. DOI: 10.1109/TNNLS.2024.3341123
- [10] J. Lim and S. Zohren, "Time-series forecasting with deep learning: A survey," *Philosophical Transactions of the Royal Society A*, vol. 379, no. 2194, pp. 1–35, 2021. DOI: 10.1098/rsta.2020.0209
- [11] Y. Kim, J. Kim, and S. Kim, "Attention-based LSTM for cryptocurrency price prediction," *IEEE Access*, vol. 10, pp. 74215–74227, 2022. DOI: 10.1109/ACCESS.2022.3189056
- [12] A. Khedr, S. Salama, and N. Yaseen, "Predicting cryptocurrency prices using deep learning and ensemble methods," *Applied Soft Computing*, vol. 104, Article 107190, 2021. DOI: 10.1016/j.asoc.2021.107190