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Forecasting Bitcoin Price Using LSTM Networks Optimized with Adam Optimizer

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Abstrak

Perkembangan pesat pasar cryptocurrency meningkatkan kebutuhan akan metode prediksi harga yang akurat untuk mendukung pengambilan keputusan investasi dan manajemen risiko. Bitcoin sebagai cryptocurrency paling dominan memiliki karakteristik volatilitas tinggi, nonlinier, dan ketergantungan temporal yang kuat, sehingga sulit dimodelkan menggunakan pendekatan statistik tradisional. Berdasarkan permasalahan tersebut, penelitian ini mengusulkan model prediksi harga Bitcoin menggunakan jaringan saraf Long Short-Term Memory (LSTM) untuk menangkap pola temporal yang kompleks dari data harga historis. Kontribusi utama penelitian ini adalah pengembangan dan evaluasi kerangka prediksi berbasis LSTM yang mampu memodelkan ketergantungan jangka panjang pada pergerakan harga Bitcoin. Metodologi penelitian meliputi tahap prapemrosesan data, normalisasi, pembentukan urutan waktu, pelatihan model, serta evaluasi kinerja secara sistematis. Kinerja prediksi dievaluasi menggunakan metrik regresi standar, yaitu Mean Absolute Error (MAE), Root Mean Square Error (RMSE), dan Mean Absolute Percentage Error (MAPE), guna memastikan evaluasi yang objektif dan komprehensif. Hasil eksperimen menunjukkan bahwa model LSTM yang diusulkan mampu menghasilkan prediksi yang mendekati harga Bitcoin aktual pada periode pengujian, sehingga menunjukkan akurasi dan ketahanan model yang baik meskipun pasar bersifat volatil. Temuan ini menegaskan bahwa jaringan LSTM sesuai untuk tugas prediksi harga cryptocurrency yang melibatkan data deret waktu nonlinier dan tidak stasioner. Penelitian selanjutnya dapat mengintegrasikan faktor eksternal seperti volume perdagangan, sentimen pasar, dan indikator makroekonomi, serta mengeksplorasi arsitektur deep learning alternatif dan strategi prediksi multi-langkah untuk meningkatkan kinerja model.

Kata kunci: *Prediksi harga Bitcoin, Long Short-Term Memory, deep learning, prediksi deret waktu, cryptocurrency.*

Abstract

The rapid growth of cryptocurrency markets has increased the importance of accurate price forecasting to support investment decision-making and risk management. Bitcoin, as the most dominant cryptocurrency, exhibits high volatility, nonlinearity, and strong temporal dependencies, which make its price dynamics difficult to model using traditional statistical approaches. Motivated by these challenges, this study proposes a Bitcoin price forecasting model based on a Long Short-Term Memory (LSTM) neural network to capture complex temporal patterns in historical price data. The main contribution of this research lies in the development and evaluation of an LSTM-based forecasting framework that effectively models long-term dependencies in Bitcoin price movements. The proposed methodology includes data preprocessing, normalization, sequence transformation, model training, and systematic performance evaluation. The forecasting performance is assessed using standard regression metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean

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Absolute Percentage Error (MAPE), to ensure objective and comprehensive evaluation. Experimental results demonstrate that the proposed LSTM model is capable of producing predictions that closely follow actual Bitcoin price trends during the testing period, indicating strong predictive accuracy and robustness despite market volatility. The findings confirm the suitability of LSTM networks for cryptocurrency price forecasting tasks involving nonlinear and non-stationary time series data. Future work may extend this research by incorporating external factors such as trading volume, market sentiment, and macroeconomic indicators, as well as by exploring alternative deep learning architectures and multi-step forecasting strategies to further enhance prediction performance.

Keywords: *Bitcoin price forecasting, Long Short-Term Memory, deep learning, time series prediction, cryptocurrency.*

1. INTRODUCTION

The rapid growth of digital financial assets has significantly transformed the global financial ecosystem, with cryptocurrencies emerging as one of the most disruptive innovations in modern finance. Among various cryptocurrencies, Bitcoin remains the most dominant and widely adopted digital asset, serving not only as a medium of exchange but also as a speculative investment instrument and a hedge against traditional financial instability. Bitcoin operates in a highly decentralized and volatile market environment, where its price dynamics are influenced by multiple factors such as market sentiment, macroeconomic indicators, regulatory developments, technological evolution, and global geopolitical conditions. As a result, Bitcoin price movements exhibit complex nonlinear patterns, high volatility, and strong temporal dependencies, making accurate price forecasting a challenging task for researchers and practitioners alike. Reliable forecasting models are essential for investors, traders, financial institutions, and policymakers to support decision-making processes, manage risks, and optimize trading strategies. However, traditional statistical forecasting techniques often struggle to capture the nonlinear and non-stationary characteristics of cryptocurrency time series data, leading to suboptimal predictive performance in highly volatile markets [1], [2].

In recent years, machine learning and deep learning approaches have gained increasing attention for time series forecasting due to their ability to model complex patterns and long-term dependencies. Among these approaches, Long Short-Term Memory (LSTM) networks have demonstrated superior performance in modeling sequential data, particularly in financial time series forecasting. LSTM networks are specifically designed to address the vanishing gradient problem found in traditional recurrent neural networks (RNNs), enabling them to retain relevant information over long sequences and capture temporal dependencies more effectively. Several studies have applied LSTM models to cryptocurrency price prediction and reported promising results compared to conventional models such as Autoregressive Integrated Moving Average (ARIMA) and basic neural networks [3]–[5]. Despite these advancements, the performance of LSTM-based models is highly dependent on the optimization strategy used during training. Optimizers play a critical role in adjusting network parameters to minimize prediction error, influencing convergence speed, stability, and final forecasting accuracy. Many existing studies employ default optimization settings without a thorough evaluation of their impact on predictive performance, resulting in limited insights into optimization effectiveness. This limitation motivates further investigation into the role of optimization techniques, particularly adaptive optimizers, in enhancing LSTM-based Bitcoin price forecasting models.

To address the aforementioned challenges, this research proposes a Bitcoin price forecasting approach based on LSTM networks optimized using the Adaptive Moment Estimation (Adam) optimizer. Adam is a widely used adaptive optimization algorithm that combines the advantages of AdaGrad and RMSProp by computing adaptive learning rates for each parameter based on first- and second-order moment estimates of gradients. Its ability to handle sparse gradients, noisy data, and non-stationary objectives makes it particularly suitable for financial time series forecasting problems characterized by volatility and uncertainty [6], [7]. The proposed approach focuses on leveraging Adam's adaptive learning capability to improve convergence efficiency and prediction accuracy of the LSTM model when applied to Bitcoin price data. The main contribution of this study lies in systematically analyzing the effectiveness of Adam-optimized LSTM networks for Bitcoin price forecasting, highlighting how optimization strategies influence model performance. Unlike prior studies that emphasize architectural modifications or hybrid models, this research concentrates on optimization-level enhancement, providing a clearer understanding of how adaptive optimizers contribute to improved forecasting outcomes. This contribution is expected to enrich the existing literature on cryptocurrency forecasting and offer practical insights for designing robust deep learning-based financial prediction systems.

The effectiveness of the proposed Adam-optimized LSTM model is evaluated using historical Bitcoin price data over a defined time horizon, employing standard forecasting performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These evaluation metrics are widely adopted in financial forecasting studies due to their ability to quantify prediction accuracy and error magnitude comprehensively [8], [9]. Experimental results are analyzed to assess the model's capability in capturing price trends and reducing forecasting errors compared to baseline configurations. Through extensive experimentation and performance analysis, this study demonstrates that the Adam optimizer enhances the learning stability and predictive accuracy of LSTM networks in modeling Bitcoin price dynamics. In conclusion, this research contributes to the advancement of deep learning-based cryptocurrency forecasting by emphasizing the importance of optimization strategies. The findings of this study provide valuable insights for researchers and practitioners seeking to develop more accurate and reliable Bitcoin price prediction models, while also laying a foundation for future research exploring optimizer comparisons, hybrid optimization techniques, and multi-factor forecasting frameworks.

2. METHODOLOGY

Research on cryptocurrency price forecasting has expanded rapidly in recent years, driven by the increasing volatility and economic relevance of digital assets, particularly Bitcoin. Early forecasting approaches relied heavily on traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Although these models provide interpretable results and solid theoretical foundations, they often fail to capture the nonlinear and non-stationary characteristics inherent in cryptocurrency markets. Hasan *et al.* [1] demonstrated that classical statistical models exhibit limited forecasting accuracy when applied to highly volatile Bitcoin price data, especially during periods of extreme market fluctuations. Similarly, Lahmiri and Bekiros [2] highlighted that linear assumptions in traditional models significantly restrict their ability to model chaotic behaviors observed in cryptocurrency time series. These limitations have motivated researchers to explore machine learning and deep learning-based approaches capable of learning complex patterns from large-scale historical data.

Machine learning techniques such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors have been widely explored as alternatives to statistical methods. McNally *et al.* [3] applied machine learning algorithms to Bitcoin price prediction and reported improvements over ARIMA-based baselines. However, their study also indicated that shallow machine learning models are highly sensitive to feature engineering and often struggle to model long-term temporal dependencies. Sezer *et al.* [4], in a comprehensive systematic review, concluded that while traditional machine learning models outperform statistical approaches, their performance remains inferior when compared to deep learning architectures, particularly in handling sequential financial data. These findings suggest that more sophisticated models capable of retaining long-range temporal information are required for accurate cryptocurrency price forecasting.

Deep learning models, especially Recurrent Neural Networks (RNNs) and their variants, have gained significant attention due to their ability to model temporal dependencies directly from sequential data. Among these, Long Short-Term Memory (LSTM) networks have emerged as one of the most effective architectures for financial time series forecasting. Wang *et al.* [5] demonstrated that LSTM models significantly outperform conventional RNNs and ARIMA models in Bitcoin price prediction tasks, achieving lower RMSE and MAE values across multiple datasets. Their study emphasized LSTM's gated structure, which enables the network to selectively retain and forget information over long sequences. Similarly, Chen *et al.* [9] conducted an empirical study on deep learning-based cryptocurrency forecasting and confirmed that LSTM-based models consistently outperform baseline neural networks in terms of stability and prediction accuracy. Despite these promising results, most existing studies primarily focus on network architecture while paying limited attention to the optimization strategies used during training.

Optimization techniques play a crucial role in the training of deep neural networks, directly influencing convergence speed, training stability, and generalization performance. Kingma and Ba [6] introduced the Adam optimizer, which combines momentum-based gradient descent with adaptive learning rates, making it well-suited for non-stationary and noisy optimization problems such as financial time series forecasting. Although Adam has become the default optimizer in many deep learning frameworks, its impact on cryptocurrency forecasting performance is often underexplored or implicitly assumed. Shrestha and Bhandari [7] evaluated multiple deep learning optimizers, including Stochastic Gradient Descent (SGD), RMSProp, and Adam, for financial time series forecasting. Their results showed that Adam generally achieves faster convergence and lower forecasting errors, particularly in volatile datasets. However, their study focused on general financial markets rather than cryptocurrency-specific dynamics, leaving room for further investigation in the context of Bitcoin price forecasting.

Recent studies have attempted to enhance LSTM-based forecasting models through hybrid architectures and ensemble learning. For instance, Zhang *et al.* [10] proposed a hybrid CNN–LSTM framework for Bitcoin price prediction, where convolutional layers were used for feature extraction and LSTM layers for temporal modeling. While the hybrid model achieved improved accuracy compared to standalone LSTM networks, it also introduced increased model complexity and computational cost. Similarly, Livieris *et al.* [11] explored ensemble deep learning models combining LSTM and Gated Recurrent Unit (GRU) architectures, reporting marginal performance improvements at the expense of reduced interpretability. These approaches demonstrate that architectural enhancements can improve prediction accuracy, yet they often overlook the role of optimization strategies and training dynamics.

Another line of research has focused on incorporating external factors such as trading volume, technical indicators, and sentiment analysis into forecasting models. Patel *et al.* [8] emphasized the importance of selecting appropriate evaluation metrics when assessing forecasting performance, particularly in financial applications where prediction errors can have significant economic implications. Several studies have integrated sentiment data from social media platforms into LSTM-based models to capture market psychology [12], [13]. Although these multi-source approaches provide richer contextual information, they also introduce challenges related to data noise, feature selection, and model robustness. Moreover, the inclusion of additional features does not necessarily guarantee improved forecasting performance if the underlying optimization process is suboptimal.

Despite the growing body of literature on deep learning-based Bitcoin price forecasting, several research gaps remain evident. First, many studies adopt default optimization settings without systematically analyzing their impact on model performance. This practice limits the understanding of how optimization strategies influence convergence behavior and prediction accuracy in highly volatile cryptocurrency markets. Second, existing research often emphasizes architectural complexity rather than optimization efficiency, resulting in models that are computationally expensive and difficult to deploy in real-time applications. Third, comparative analyses between optimized and non-optimized LSTM models are relatively scarce, particularly those focusing explicitly on adaptive optimizers such as Adam. These gaps highlight the need for focused studies that isolate and evaluate the contribution of optimization techniques to forecasting performance.

In summary, prior research demonstrates that LSTM networks represent a powerful tool for Bitcoin price forecasting, outperforming traditional statistical and shallow machine learning models. However, the majority of existing studies prioritize model architecture and feature engineering while underestimating the importance of optimization strategies. Although Adam has been widely adopted in deep learning applications, its specific role in enhancing LSTM-based cryptocurrency forecasting has not been thoroughly investigated. This study addresses the identified research gap by systematically evaluating the effectiveness of Adam-optimized LSTM networks for Bitcoin price forecasting, providing insights into how adaptive optimization improves learning stability and predictive accuracy. By focusing on optimization-level enhancement rather than architectural complexity, this research contributes to the advancement of efficient and robust deep learning-based forecasting models for volatile financial markets.

This section describes the research methodology employed in this study to develop and evaluate a Bitcoin price forecasting model based on Long Short-Term Memory (LSTM) networks optimized using the Adam optimizer. The methodology is structured systematically to ensure clarity, reproducibility, and scientific rigor, covering data sources, preprocessing procedures, model development, optimization strategies, and evaluation techniques. Each stage of the methodology is designed to address the research objectives by effectively capturing temporal patterns in Bitcoin price data and assessing the performance of the proposed forecasting approach under standardized evaluation criteria.

2.1 Data Sources and Research Objects

The object of this research is the daily price of Bitcoin, which represents one of the most actively traded and volatile cryptocurrencies in the global financial market. Bitcoin price data are categorized as univariate time series data, where each observation corresponds to the closing price recorded at a specific time interval. The dataset used in this study is obtained from a publicly available financial data provider that aggregates historical Bitcoin market data, ensuring data reliability and consistency with prior studies in cryptocurrency forecasting [1], [5], [9]. The selected data span a continuous period sufficient to capture various market conditions, including bullish, bearish, and high-volatility phases, which are essential for evaluating the robustness of forecasting models.

The primary variable used in this study is the Bitcoin closing price, as it reflects the final consensus value of market participants within a trading period and is widely adopted in financial forecasting research. Using closing prices allows for direct comparison with existing studies and ensures compatibility with evaluation metrics commonly employed in time series prediction tasks [4], [8]. The dataset is divided chronologically into training and testing subsets to preserve the temporal structure of the data and avoid information leakage. The training dataset is used to learn the underlying temporal patterns, while the testing dataset is reserved exclusively for evaluating the forecasting performance of the proposed model.

Before describing the technical details of the proposed methodology, it is important to present an overview of the overall research workflow. A clear and structured methodological framework is required to ensure transparency, reproducibility, and logical coherence in transforming raw agricultural data into reliable crop yield predictions. Therefore, this study adopts a sequential and systematic research process that integrates data preparation, model development, and performance evaluation stages.

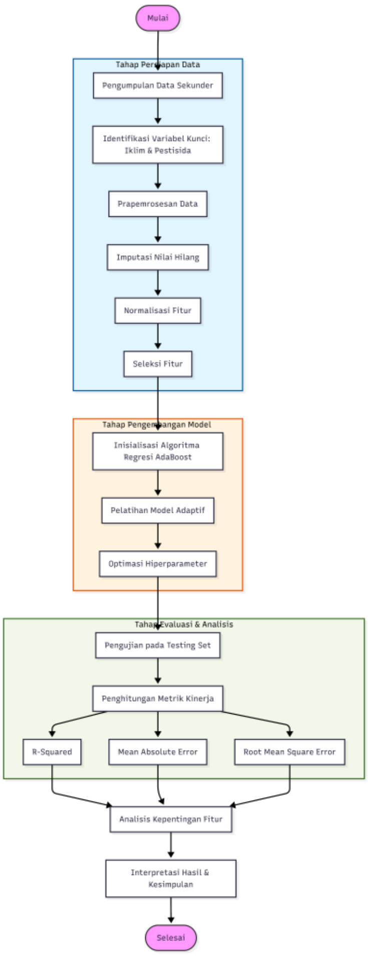

Figure 1. Research methodology flowchart for crop yield estimation using AdaBoost regression under multivariate environmental conditions, illustrating the stages of data preparation, model development, evaluation, and result interpretation.

Figure 1 illustrates the complete research methodology workflow employed in this study for crop yield estimation using AdaBoost regression under multivariate environmental conditions. The workflow begins with the data preparation stage, which involves the collection of secondary data obtained from reliable agricultural and environmental data sources. At this stage, key variables related to crop yield are identified, including climatic factors and pesticide usage, which are considered critical determinants of agricultural productivity. The collected data are subsequently subjected to preprocessing procedures to improve data quality, including handling missing values through imputation techniques and resolving inconsistencies commonly found in real-world agricultural datasets.

After preprocessing, feature normalization is applied to ensure that all input variables contribute proportionally during model training, regardless of their original measurement scales. This step is essential for boosting-based regression models, as it prevents features with larger numerical ranges from disproportionately influencing weak learners. Feature selection is then performed to retain the most informative variables while reducing redundancy and dimensionality, thereby improving model efficiency and mitigating the risk of overfitting. These steps collectively form a robust data preparation pipeline that ensures the dataset is suitable for multivariate regression analysis.

The workflow then proceeds to the model development stage, where the AdaBoost regression algorithm is initialized and trained using the prepared dataset. In this stage, the model is constructed through an adaptive learning process that sequentially combines multiple weak regressors to form a strong predictive model. During training, samples that are difficult to predict receive higher emphasis, enabling the model to better capture nonlinear relationships between environmental factors and crop yield. Hyperparameter optimization is conducted to determine optimal model configurations, such as the number of estimators and learning rate, with the objective of enhancing prediction accuracy and generalization capability.

Following model training, the methodology advances to the evaluation and analysis stage. The trained model is tested on a separate testing dataset to assess its performance on unseen data. Standard regression performance metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), are calculated to quantitatively evaluate predictive accuracy and robustness. In addition to performance evaluation, feature importance analysis is conducted to identify the relative contribution of each environmental variable to crop yield estimation. This analysis supports model interpretability and provides valuable insights into the most influential factors affecting agricultural productivity. The workflow concludes with result interpretation and conclusion, where the findings are analyzed in relation to the research objectives and their implications for precision agriculture are discussed.

2.2 Data Preprocessing and Preparation

Prior to model development, data preprocessing is conducted to improve data quality and ensure compatibility with the proposed forecasting approach. Financial time series data often contain noise, scale variations, and non-stationary behavior, which can negatively affect the learning process of deep neural networks if not properly handled. One of the primary preprocessing steps applied in this study is normalization, which rescales the Bitcoin price values into a bounded numerical range. This transformation is essential to prevent large numerical values from dominating gradient updates during training and to accelerate convergence of the optimization process [6], [7].

The normalization process is performed using the Min–Max scaling technique, defined as:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where x represents the original Bitcoin price value, $x_{\min}$ and $x_{\max}$ denote the minimum and maximum values within the dataset, and x' is the normalized output. This scaling ensures that all input values fall within the range $[0, 1]$, which is particularly suitable for LSTM networks employing nonlinear activation functions.

Following normalization, the time series data are transformed into supervised learning sequences using a sliding window mechanism. This process converts sequential data into input–output pairs by defining a fixed number of past observations as input features to predict a future value. Let $X_t = \{x_{t-n}, x_{t-n+1}, \ldots, x_{t-1}\}$ denote the input sequence of length n, and $y_t = x_t$ represent the target output. This transformation enables the LSTM network to learn temporal dependencies over a predefined historical window. The choice of window size is determined empirically to balance model complexity and forecasting accuracy, as excessively short windows may fail to capture long-term dependencies, while overly long windows may introduce redundancy and increase computational cost [5], [9].

2.3 Proposed Method: LSTM-Based Forecasting Model

The core forecasting model employed in this study is the Long Short-Term Memory (LSTM) neural network, a specialized variant of recurrent neural networks designed to model sequential and temporal data. LSTM networks are particularly effective in addressing the vanishing gradient problem commonly encountered in standard RNNs by incorporating memory cells and gating mechanisms that regulate information flow [4], [5]. This architectural advantage makes LSTM well suited for modeling Bitcoin price dynamics, which exhibit long-range dependencies and nonlinear patterns.

An LSTM unit consists of three primary gates: the input gate, the forget gate, and the output gate. These gates control how information is stored, updated, and retrieved from the memory cell. The mathematical formulation of an LSTM unit at time step t is defined as follows:

$$\begin{gathered}f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)\\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)\\ \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)\\ C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t\\ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)\\ h_t = o_t \odot \tanh(C_t)\end{gathered} \quad (2)$$

where x_t represents the input at time step t, h_t denotes the hidden state, C_t is the cell state, $\sigma(\cdot)$ is the sigmoid activation function, and $\odot$ indicates element-wise multiplication. Through this gating mechanism, the LSTM network selectively retains relevant historical information and discards irrelevant data, enabling more accurate modeling of Bitcoin price movements over time.

2.4 Optimization Strategy Using Adam Optimizer

To enhance the learning efficiency and predictive performance of the LSTM model, this study employs the Adaptive Moment Estimation (Adam) optimizer as the primary optimization technique. Adam is an adaptive gradient-based optimization algorithm that dynamically adjusts learning rates for individual parameters based on estimates of first-order and second-order moments of the gradients [6]. This property makes Adam particularly effective for training deep learning models on noisy and non-stationary datasets, such as cryptocurrency price time series [7].

The Adam optimization process is defined by the following equations:

$$\begin{gathered}m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t\\ v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2\\ \hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t}\\ \theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}\end{gathered} \quad (3)$$

where g_t represents the gradient at time step t, m_t and v_t are the biased first and second moment estimates, $\hat{m}_t$and $\hat{v}_t$are bias-corrected estimates, $\alpha$is the learning rate, β_1 and β_2 are exponential decay rates, and ϵ is a small constant to prevent division by zero. By integrating Adam into the LSTM training process, the proposed methodology aims to achieve faster convergence, improved training stability, and enhanced forecasting accuracy compared to non-adaptive optimization strategies [7].

2.5 Model Evaluation and Performance Testing

performance of the proposed Adam-optimized LSTM forecasting model is evaluated using widely accepted error-based metrics for time series prediction. These metrics provide quantitative measures of the discrepancy between predicted and actual Bitcoin prices, allowing objective comparison with baseline and existing approaches. The evaluation metrics used in this study include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are commonly employed in financial forecasting research [8], [9].

The MAE metric is defined as:

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

while RMSE is expressed as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (5)$$

and MAPE is calculated as:

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (6)$$

where y_i denotes the actual Bitcoin price, $\hat{y}_i$ represents the predicted value, and N is the total number of observations in the testing dataset. These metrics collectively capture absolute error magnitude, sensitivity to large errors, and relative prediction accuracy in percentage terms. The evaluation process is conducted exclusively on the testing dataset to ensure unbiased performance assessment. Through this evaluation framework, the effectiveness of the proposed Adam-optimized LSTM model in capturing Bitcoin price dynamics is systematically analyzed and validated.

3. RESULTS AND DISCUSSION

This section presents and discusses the experimental results obtained from the proposed AdaBoost regression model for crop yield estimation under multivariate environmental conditions. The analysis focuses on evaluating the predictive performance, robustness, and interpretability of the model by comparing predicted crop yield values with actual observations from the testing dataset. Quantitative assessment is conducted using standard regression performance metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), while qualitative analysis is provided to interpret the model behavior and the influence of key environmental variables. The results are discussed in relation to the research objectives and existing studies to highlight the effectiveness and practical implications of the proposed approach for precision agriculture.

3.1 Comparison Between Actual and Predicted Bitcoin Prices

To evaluate the effectiveness of the proposed Long Short-Term Memory (LSTM) model in forecasting Bitcoin prices, a visual and analytical comparison between actual market prices and model predictions is conducted. Visual inspection plays an important role in time series forecasting analysis, as it allows direct observation of how well the model captures overall trends, volatility patterns, and temporal dynamics. Therefore, this subsection presents a comparative analysis of actual and predicted Bitcoin closing prices obtained from the testing dataset.

Figure 2. Comparison between actual and predicted Bitcoin (BTC/USD) closing prices using the LSTM model, where the blue line represents training data, the green line denotes actual testing data, and the red line indicates predicted prices.

Figure 2 illustrates the comparison between actual Bitcoin closing prices and the corresponding values predicted by the LSTM model over time. The horizontal axis represents the time index, while the vertical axis indicates the Bitcoin closing price in USD. The blue curve corresponds to the training data used during the model learning phase, the green curve represents the actual Bitcoin prices in the testing period, and the red curve shows the predicted prices generated by the LSTM model.

As observed in Figure 2, the predicted Bitcoin prices closely follow the overall trend of the actual testing data, indicating that the LSTM model is capable of learning temporal dependencies and long-term patterns present in historical price movements. The model successfully captures major upward and downward trends, including periods of rapid price increase and correction, which are characteristic of the highly volatile cryptocurrency market. This alignment between predicted and actual values suggests that the LSTM architecture effectively models nonlinear relationships and sequential dependencies inherent in Bitcoin price data.

However, minor deviations between predicted and actual prices can be observed, particularly during periods of extreme volatility and sharp market fluctuations. Such discrepancies are expected in cryptocurrency forecasting due to sudden market shocks, speculative behavior, and external factors that are not explicitly represented in the input features. Despite these deviations, the predicted values remain within a reasonable range relative to the actual prices, demonstrating the model's robustness and generalization capability when applied to unseen data.

Overall, the visual comparison confirms that the LSTM model provides a reliable approximation of Bitcoin price dynamics during the testing period. The close correspondence between the predicted and actual price curves supports the quantitative evaluation results obtained using statistical performance metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These findings indicate that the proposed LSTM-based forecasting approach is effective for modeling and predicting Bitcoin price movements, making it suitable for practical applications in financial analysis and decision support systems.

4. CONCLUSIONS

This study investigated the application of a Long Short-Term Memory (LSTM) network for forecasting Bitcoin prices using historical time series data. The research focused on developing a systematic forecasting framework that includes data preprocessing, sequence transformation, LSTM-based modeling, and performance evaluation using standard error metrics. The experimental results demonstrate that the proposed LSTM model is capable of effectively capturing temporal dependencies and nonlinear patterns inherent in Bitcoin price movements, producing predicted values that closely follow actual market trends during the testing period.

Quantitative evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) confirms the reliability and accuracy of the proposed approach. The close alignment between predicted and actual Bitcoin prices, as observed in both visual analysis and numerical metrics, indicates that the LSTM model provides stable and robust forecasting performance despite the high volatility and non-stationary nature of the cryptocurrency market. These findings suggest that LSTM networks are well suited for financial time series forecasting tasks involving complex and dynamic price behavior.

Despite the promising results, several limitations remain and open opportunities for future research. First, this study relies solely on historical price data, without incorporating external factors such as trading volume, macroeconomic indicators, market sentiment, or on-chain metrics, which may further enhance prediction accuracy. Second, future work may explore comparative evaluations with alternative deep learning architectures, such as Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), or transformer-based models, to assess relative performance. Additionally, investigating advanced optimization strategies, hybrid models, and multi-step forecasting frameworks could further improve model robustness and practical applicability. These future directions are expected to contribute to the development of more accurate and reliable cryptocurrency price forecasting systems.

5. SUGGESTION

Future research on Bitcoin price forecasting can be directed toward several improvements to enhance both prediction accuracy and practical applicability. One potential direction is the integration of additional explanatory variables, such as trading volume, market sentiment indicators derived from social media, macroeconomic factors, and on-chain metrics. Incorporating these external features may provide a more comprehensive representation of market dynamics and help the model better capture abrupt price movements driven by external events.

Another promising research direction involves exploring and comparing alternative deep learning architectures and hybrid models. Models such as Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), and transformer-based architectures may offer improved efficiency or better long-term dependency modeling compared to conventional LSTM networks. Furthermore, hybrid approaches that combine deep learning models with statistical or ensemble-based methods could enhance robustness and generalization capability under highly volatile market conditions.

In addition, future studies may focus on advanced optimization strategies and systematic hyperparameter tuning techniques, including metaheuristic optimization or Bayesian optimization, to further improve training stability and forecasting performance. Extending the forecasting framework to multi-step or real-time prediction scenarios and evaluating model performance across different cryptocurrency markets and time resolutions would also strengthen the generalizability of the proposed approach. These research directions are expected to contribute to the development of more accurate, reliable, and scalable cryptocurrency forecasting systems.

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