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Predicting Bitcoin and Ethereum Prices Using the Long Short- Term Memory (LSTM) Model

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Abstract

Cryptocurrency is a highly volatile digital asset, necessitating accurate and adaptive forecasting methods. This study implements a Long Short-Term Memory (LSTM) model to predict the daily closing prices of two leading cryptocurrencies Bitcoin (BTC) and Ethereum (ETH) using historical data from Yahoo Finance and Binance. To enhance data richness and model robustness, datasets from both sources were vertically merged. The methodological framework included data preprocessing, Min–Max normalization, formation of 24-day sliding input windows, and training across three data split ratios (70:30, 80:20, and 90:10). Model performance was evaluated using the Root Mean Squared Error (RMSE). Results indicate that the LSTM model achieved high prediction accuracy, with the lowest RMSE values of 0.0137 for BTC and 0.0152 for ETH using the combined dataset with a 90:10 split. Beyond modeling, a web-based application was developed using Streamlit, enabling users to perform real-time predictions and export results. This study contributes to the field of cryptocurrency forecasting by demonstrating that multi-source data integration significantly improves predictive accuracy and model generalization. The proposed framework offers both theoretical insights and practical tools for researchers and investors in financial technology.

Keywords: Cryptocurrency, Bitcoin, Ethereum, LSTM, Price Prediction

1. INTRODUCTION

The evolution of global financial technology has been driven by the emergence of cryptocurrency as a disruptive innovation. This digital currency, built on blockchain technology, introduces decentralization and peer-to-peer transactions without intermediaries, providing users with improved autonomy, transparency, and security compared to conventional financial systems [1], [2]. By eliminating the need for centralized authorities such as banks or governments, blockchain technology redefines trust in financial transactions, offering a more democratized and secure alternative that continues to gain traction across industries and global markets.

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Among the various digital assets, Bitcoin (BTC) and Ethereum (ETH) are the two most dominant cryptocurrencies that form the backbone of the modern blockchain economy. Bitcoin, introduced in 2009 by Satoshi Nakamoto, is widely referred to as digital gold because of its limited supply of 21 million coins, which protects it from inflation and maintains long-term value stability [3], [4]. Meanwhile, Ethereum, launched in 2015 by Vitalik Buterin, extends blockchain functionality by introducing smart contracts and decentralized applications (DApps), enabling developers to create transparent, automated, and secure digital ecosystems [5]. This programmable layer gives Ethereum a unique position in the blockchain hierarchy, supporting a wide range of applications beyond simple financial transactions.

Despite their technological advantages and increasing adoption, one of the major challenges in cryptocurrency trading is extreme price volatility. The prices of cryptocurrencies are heavily influenced by speculative activity, changes in regulatory policy, shifts in public sentiment, and the rapid pace of technological development [6]. This inherent instability increases market uncertainty and investor risk, which in turn motivates the development of intelligent and adaptive forecasting models to aid in data-driven investment decision-making [7], [8]. Without such predictive tools, traders and investors are left vulnerable to sudden market shifts that could lead to significant financial losses.

To address these challenges, researchers have turned to various forecasting methodologies. Traditional statistical models, such as the Autoregressive Integrated Moving Average (ARIMA), often struggle to model the non-linear and sequential nature of financial time-series data. In contrast, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in capturing long-term temporal patterns in complex datasets [9], [10]. As a variant of Recurrent Neural Networks (RNN), LSTM networks are specifically designed to address issues such as the vanishing gradient problem, allowing them to retain and process information across extended sequences, which significantly enhances their predictive accuracy for financial time series [11], [12].

Several studies have already validated the effectiveness of LSTM models for cryptocurrency price prediction. For example, [13] utilized Bitcoin data from Yahoo Finance and achieved promising results in short-term forecasting, though the scope of the study was confined to a single dataset. Similarly, [14] demonstrated that using a 20–30-day input window yields more stable and accurate forecasts, while studies such as [6], [9] confirmed that LSTM models are particularly adept at capturing the non-linear fluctuations characteristic of Bitcoin's price movements. These findings underscore the potential of LSTM as a powerful tool for forecasting in volatile and data-rich environments like the cryptocurrency market.

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However, a common limitation across many of these studies is their focus on single-asset or single-source datasets. This narrow approach may compromise the generalizability and robustness of the forecasting models, potentially leading to biased or overfitted results. To overcome this limitation, the present study integrates multi-source data from Yahoo Finance and Binance for two major cryptocurrencies, Bitcoin and Ethereum, with the aim of developing a more comprehensive and robust predictive model. In addition to leveraging a more diverse dataset, the study employs data preprocessing techniques such as Min–Max scaling to normalize inputs and utilizes performance evaluation metrics like Root Mean Squared Error (RMSE) to assess model accuracy and interpretability [15], [16].

The objectives of this research are threefold: (1) to analyze the predictive capability of LSTM in forecasting daily Bitcoin and Ethereum prices, (2) to evaluate the effect of combining data from Yahoo Finance and Binance on prediction accuracy, and (3) to develop an interactive web-based prediction platform that visualizes results in real time. The main contributions of this study include the integration of multiple data sources and digital assets into a unified LSTM-based forecasting framework, the enhancement of model reliability and interpretability through appropriate scaling and evaluation metrics, and the deployment of a user-friendly web application for practical financial forecasting use cases.

2. METHODS

This study was conducted over a three-month period from February to April 2025 and employed a structured methodology encompassing data acquisition, preprocessing, model development, performance evaluation, and real-time system deployment. To ensure robustness and comprehensiveness, eighteen experimental scenarios were formulated by combining two cryptocurrency assets (Bitcoin and Ethereum), three data sources (Yahoo Finance, Binance, and a merged dataset), and three distinct training-to-testing data split ratios (70:30, 80:20, and 90:10). The complete research workflow is illustrated in Figure 1, outlining the sequential process from data collection to web-based application deployment.

Figure 1. Overall research framework for LSTM-based cryptocurrency price prediction.

2.1 Data Collection and Preprocessing

Historical daily market data—specifically, the Open, Close, and Volume fields for Bitcoin and Ethereum were retrieved from Yahoo Finance and Binance, covering

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a five-year period from January 2020 to January 2025. Since the primary objective of the study is to predict future closing prices, only the Date and Close columns were retained for model training. To ensure data consistency and cross-platform comparability, an extensive preprocessing pipeline was implemented.

The raw datasets were initially subjected to a data cleaning process. Records were inspected for missing, duplicated, or erroneous entries that could compromise model accuracy. Missing values were imputed using linear interpolation to maintain the temporal continuity of the time series and to avoid abrupt transitions. Following this, both Yahoo Finance and Binance data were synchronized based on their respective timestamps. This alignment step addressed discrepancies due to varying time zones and trading session cutoffs. Normalization of the time indices and date reindexing were performed to ensure uniform alignment across sources. The combined dataset was constructed by vertically concatenating Yahoo and Binance entries while preserving their chronological integrity. This fusion strategy increased dataset diversity while retaining individual source characteristics. Minor variations in record counts and outlier values, primarily caused by exchange rate discrepancies, were resolved using statistical smoothing and resampling techniques [17].

Once data consistency was achieved, sequential input-output pairs were generated using a 24-day sliding window approach [18]. This technique transformed the normalized closing prices into supervised learning sequences, allowing the model to capture short-term dependencies and seasonal patterns over approximately one month of trading data. LSTM networks are particularly sensitive to input scale, and therefore, Min–Max normalization was applied to rescale all closing price values to a range between 0 and 1, using the standard formula as shown in Equation [15].

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

This normalization ensures uniform feature scaling across different sources, accelerates convergence during training, and improves model stability [19].

2.2 LSTM Model Architecture and Training

The core prediction model employed in this study is based on the Long Short-Term Memory (LSTM) architecture, implemented using TensorFlow and Keras libraries. The model was purpose-built to capture non-linear relationships and long-range temporal dependencies inherent in cryptocurrency time-series data. Figure 2 illustrates the structure of the model and its component layers.

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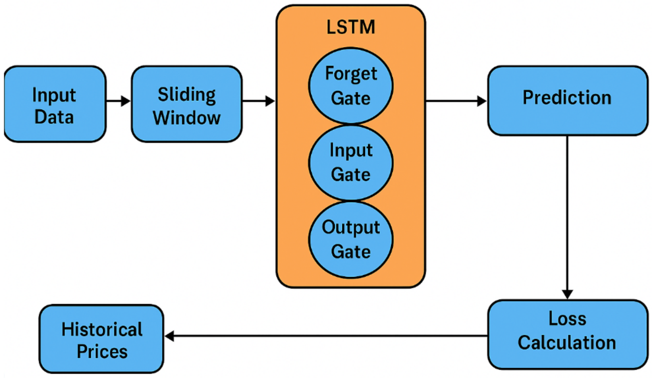

Figure 2. LSTM Model Architecture

The architecture begins with an input layer that accepts sequences shaped as (24,1), representing 24 consecutive days of closing price data per input window. This is followed by a single LSTM hidden layer comprising 64 memory units. Each unit contains three internal gates—Forget, Input, and Output—that regulate information flow, thus allowing the network to retain relevant patterns while discarding noise [20]. A dropout rate of 0.2 was applied to mitigate overfitting by randomly disabling neurons during training iterations. The final layer is a dense (fully connected) output layer with a single neuron using a linear activation function, which returns the predicted closing price.

The model was compiled with the Mean Squared Error (MSE) as the loss function and optimized using the Adam optimizer, configured with a learning rate of 0.005. The network was trained over 100 epochs with a batch size of 16. To prevent unnecessary computation and potential overfitting, early stopping was implemented with a patience value of 10—halting training once validation loss plateaued across successive epochs. A schematic overview of the end-to-end modelling workflow—from data preparation to prediction generation is presented in Figure 3, depicting the proposed LSTM-based cryptocurrency price prediction framework.

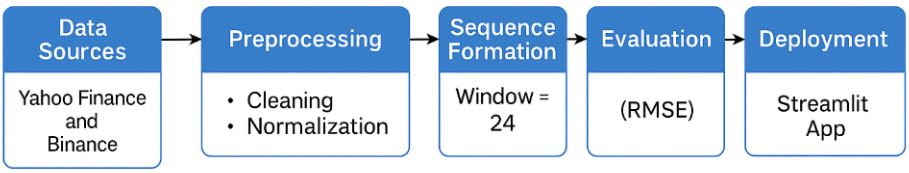

Figure 3. Proposed LSTM-based Cryptocurrency Price Prediction Framework

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2.3 Model Evaluation

To evaluate the predictive performance of the trained LSTM model, Root Mean Squared Error (RMSE) was used as the primary accuracy metric. RMSE quantifies the average magnitude of prediction errors and is defined as shown in Equation 2.

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

where y_i represents the actual closing price, $\hat{y}_i$ denotes the predicted value, and n is the total number of predictions.

Lower RMSE values indicate higher predictive accuracy. The model's performance was evaluated across various experimental conditions—three train-test splits (70:30, 80:20, 90:10), three data source configurations (Yahoo Finance, Binance, and Combined), and both cryptocurrency assets (BTC and ETH). This experimental diversity offers a comprehensive understanding of how data quantity and diversity influence model robustness, generalizability, and predictive power.

2.4 System Implementation

To translate the research findings into a usable tool, a web-based forecasting application was developed using the Streamlit framework. The application integrates the trained LSTM model into an interactive interface that allows users to upload new input data, visualize real-time predictions, and export the results in CSV format for further analysis. Additionally, the platform includes a built-in currency conversion feature that enables users to convert predicted prices from USD to IDR, enhancing the tool's utility for regional investors.

This system bridges the gap between theoretical research and practical application by providing investors, data scientists, and financial analysts with an accessible and intuitive platform for cryptocurrency forecasting. By enabling real-time analysis and dynamic visualization, the web app fosters informed decision-making in high-volatility digital asset markets [21].

3. RESULTS AND DISCUSSION

This section presents the quantitative results of model evaluation, visualization of prediction outcomes, and discussion of the findings in the context of existing studies. It also demonstrates the practical implementation of the LSTM-based prediction model through a web application.

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3.1. Quantitative Evaluation

The LSTM model's performance was assessed using the Root Mean Squared Error (RMSE) metric, which measures the average magnitude of prediction errors. Evaluations were conducted across 18 experimental scenarios that varied in three main dimensions: cryptocurrency type (Bitcoin or Ethereum), data source (Yahoo Finance, Binance, and Combined), and train-test split ratios (70:30, 80:20, and 90:10). As summarized in Table 1, the RMSE values provide a clear indication of how these factors influence model accuracy.

Table 1. RMSE Values of the LSTM Model Based on Dataset and Split Ratio

Aset & Source	Ratio Split	RMSE
BTC_Yahoo	70:30	0.0211
BTC_Yahoo	80:20	0.0187
BTC_Yahoo	90:10	0.0153
BTC_Binance	70:30	0.0234
BTC_Binance	80:20	0.0206
BTC_Binance	90:10	0.0175
BTC_Combined	70:30	0.0188
BTC_Combined	80:20	0.0162
BTC_Combined	90:10	0.0137
ETH_Yahoo	70:30	0.0234
ETH_Yahoo	80:20	0.0202
ETH_Yahoo	90:10	0.0169
ETH_Binance	70:30	0.0257
ETH_Binance	80:20	0.0226
ETH_Binance	90:10	0.0194
ETH_Combined	70:30	0.0201
ETH_Combined	80:20	0.0178
ETH_Combined	90:10	0.0152

The analysis of RMSE values across all experimental configurations reveals several key findings related to the impact of training data size, data source diversity, and asset-specific performance. Firstly, the proportion of training data plays a significant role in improving prediction accuracy. Across all datasets and sources, the 90:10 split consistently resulted in the lowest RMSE values for both Bitcoin and Ethereum. This outcome confirms that increasing the volume of training data allows the LSTM model to better capture underlying temporal dependencies, leading to improved generalization on unseen data [22].

Secondly, the use of combined data sources had a noticeable positive effect on model performance. The merged dataset, which integrates historical price data from both Yahoo Finance and Binance, consistently outperformed single-source

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datasets in all split ratios. Notably, the best overall RMSE 0.0137 was achieved using the BTC combined dataset with a 90:10 split. This suggests that the heterogeneity and breadth of information captured through multi-source integration provide a richer learning environment for the model, allowing it to adapt to a wider range of market behaviors and anomalies.

Lastly, a comparative evaluation between Bitcoin and Ethereum forecasts shows that Bitcoin prices were predicted slightly more accurately than those of Ethereum. This discrepancy may be attributed to Bitcoin's larger market capitalization, higher liquidity, and more stable price movement, which together result in less volatile and more predictable patterns. Such characteristics align well with the strengths of LSTM networks, which excel in learning from smooth, time-dependent sequences [23].

To visually support these findings, RMSE heatmaps were generated, as illustrated in Figure 4. These heatmaps highlight the distribution of RMSE values across different combinations of data sources and split ratios for both BTC and ETH. The graphical representation clearly shows a consistent decrease in prediction error as the proportion of training data increases and as the model is trained on combined datasets, further validating the quantitative results. Figure 4. Heatmaps illustrating the RMSE values for Bitcoin (BTC) and Ethereum (ETH) across different data sources (Yahoo Finance, Binance, Combined) and train-test split ratios (70:30, 80:20, 90:10). The visualizations demonstrate a clear trend of decreasing prediction error with increased training data and combined data sources, highlighting the model's improved accuracy and generalization capacity under optimal configurations.

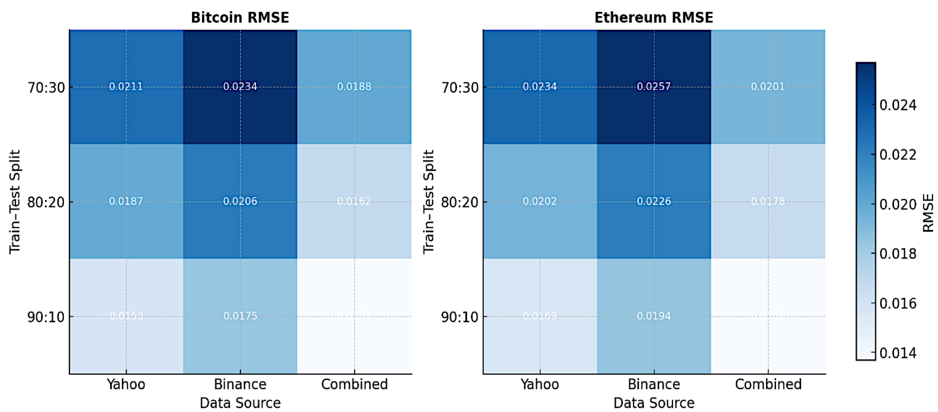

Figure 4. BTC–ETH RMSE Heatmap

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3.2. Prediction Visualization

To further validate the model's predictive performance, visual comparisons were conducted between the actual and predicted cryptocurrency prices on the test datasets. These comparisons serve not only to complement the RMSE-based quantitative evaluations but also to provide an intuitive understanding of the model's behavior in forecasting real market trends. Figures 5 and 6 present the prediction visualizations for the best-performing experimental scenarios: the combined datasets for Bitcoin and Ethereum using the 90:10 train-test split, which achieved the lowest RMSE values (0.0137 for BTC and 0.0152 for ETH, respectively).

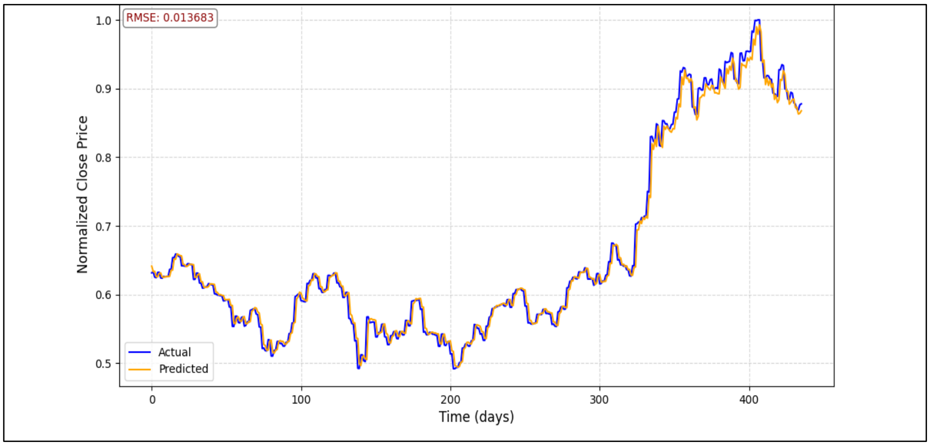

Figure 5. Prediction vs. Actual Graph for BTC Combined (Ratio 90:10, RMSE: 0.0137)

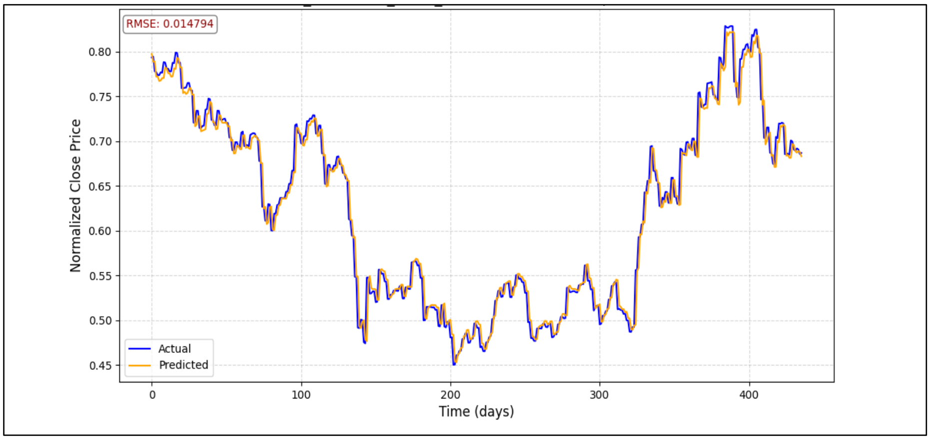

Figure 6. Prediction vs. Actual Graph for ETH Combined (Ratio 90:10, RMSE: 0.0152)

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In Figure 5 and 6, the blue line represents the actual closing prices obtained from the test set, while the orange line corresponds to the predicted prices generated by the trained LSTM model. The plots clearly show that the model is able to closely follow the trajectory of actual price movements over time. This is particularly evident in the Bitcoin forecast, where the predicted line tracks the real trend with minimal lag and maintains high fidelity to the overall direction and shape of the price curve. The model demonstrates a strong ability to anticipate both upward and downward trends, capturing the cyclical nature and temporal dependencies of Bitcoin's price behavior.

Similarly, the Ethereum prediction graph shows a high degree of alignment between actual and forecasted values. Although the ETH predictions display slightly more variability and lag compared to BTC especially around local peaks and troughs the LSTM model still effectively replicates the general movement and inflection points of the price series. This slight discrepancy may be attributed to Ethereum's comparatively higher price volatility and lower market stability, which can present greater challenges for time-series forecasting models.

These visual results reinforce the model's generalization capability and its suitability for real-time market forecasting applications. The LSTM architecture, when trained on sufficiently large and diverse datasets, is capable of modeling complex, non-linear patterns in financial time series with notable accuracy. The visual consistency between actual and predicted lines also suggests that the model is not simply overfitting to training data but is genuinely learning the underlying temporal structure of cryptocurrency price movements.

3.3. Application of Model Prediction

In addition to theoretical development and empirical evaluation, this study emphasizes practical applicability through the deployment of a real-time web-based forecasting tool. The application, built using the Streamlit framework, successfully integrates the trained LSTM model and provides an intuitive interface for users to generate cryptocurrency price predictions dynamically. Figure 7 displays the user interface of the deployed system, which allows for interactive input, live predictions, data visualization, and export functionality.

This implementation demonstrates that the contributions of the research extend beyond academic insights and offer tangible, real-world utility. Users—including traders, financial analysts, and researchers—can interact with the application to upload new datasets, forecast future prices of Bitcoin and Ethereum, convert values from USD to IDR for regional relevance, and download results in CSV format for further analysis. Such capabilities make the platform suitable for both educational purposes and decision support in financial environments.

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Beyond the technical deployment, a deeper discussion of the model's performance highlights several critical findings regarding the influence of data-centric strategies on forecasting outcomes. First, asset type plays a significant role in prediction accuracy. As the results indicate, the model consistently performs better on Bitcoin than Ethereum. This is likely due to Bitcoin's higher liquidity, trading volume, and historical stability, which result in more consistent temporal patterns. Ethereum, by contrast, is subject to greater price volatility and market fluctuations, making it inherently more difficult to model using sequence-based approaches. Second, the volume of training data significantly affects the model's generalization capacity. The experiments clearly show that a 90:10 training-to-testing split consistently produces lower RMSE values, reaffirming the fundamental machine learning principle that models benefit from more extensive training data. Larger datasets allow the LSTM network to better learn cyclical trends, noise tolerance, and abrupt transitions commonly seen in financial time series.

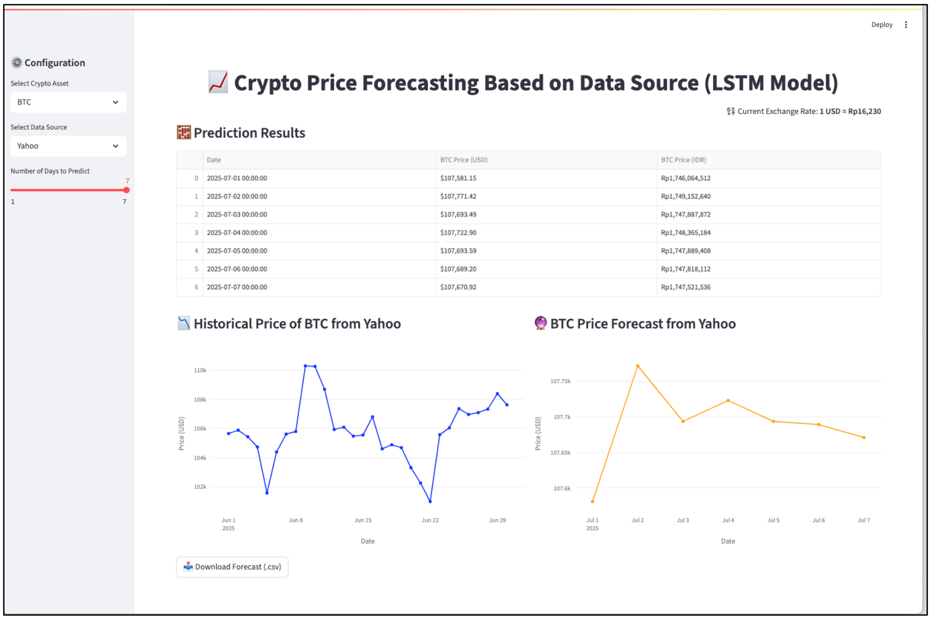

Figure 7. User Interface of the Streamlit-based Prediction Application

However, the most critical and novel contribution of this study lies in the impact of data source diversity. The integration of multiple data providers Yahoo Finance and Binance resulted in significantly improved performance over single-source models. By combining data, the model benefits from a broader and more nuanced representation of market conditions, mitigating source-specific biases, and enriching its exposure to diverse trading behaviors. This enhanced diversity contributes directly to the model's robustness and its ability to generalize across different market phases. Taken together, these findings confirm that the success

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of the LSTM model depends not only on the sophistication of its architecture but also on strategic choices in data acquisition and preparation. The study underscores that selecting the right type of asset, utilizing ample training data, and employing multiple data sources are all pivotal in maximizing forecasting performance.

3.4. Discussion

The findings of this study affirm that the integration of multi-source data significantly enhances the performance of LSTM-based models in forecasting cryptocurrency prices. Specifically, combining historical data from Yahoo Finance and Binance provided richer temporal signals and minimized source-specific bias, ultimately leading to better model generalization. This result aligns with established machine learning principles, where diversity and volume of training data are often more influential than model complexity alone in achieving robust predictive performance. The enhanced accuracy observed in this study particularly in the BTC Combined dataset using a 90:10 split demonstrates the practical value of multi-source integration in financial forecasting contexts.

Comparing these findings to prior research highlights notable methodological advancements. For instance, [13] relied solely on Yahoo Finance data and achieved relatively higher RMSE values, a likely consequence of limited data diversity. Similarly, the study by [17] focused exclusively on short-term Bitcoin price prediction using a single platform, thereby restricting the model's exposure to broader market behaviors. By contrast, the present study expands the forecasting scope by integrating two digital assets (BTC and ETH) and merging datasets from two major financial data sources. This comprehensive data strategy not only reduced RMSE values across scenarios but also demonstrated superior adaptability to different asset volatilities and market phases.

Despite the model's strong performance, several limitations were identified that present opportunities for future enhancement. First, while the LSTM architecture proved effective under normal market conditions, its prediction accuracy declined slightly during periods of extreme volatility. This is particularly evident near market peaks and sudden price drops, where the model's outputs exhibit lag or underreaction. These scenarios are challenging for most time-series models, especially those relying solely on historical price data without additional contextual inputs.

Second, the current model utilizes only the closing price as the predictive feature, omitting potentially valuable indicators such as trading volume, open-high-low-close (OHLC) data, and macroeconomic or sentiment variables. Excluding these factors may limit the model's ability to respond to external market shocks or behavioral trends, particularly in an asset class as sentiment-driven as

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cryptocurrency. Studies incorporating sentiment analysis from sources like Twitter, Reddit, or news aggregators have shown improvements in short-term prediction accuracy [24]. Integrating such features could enhance the model's responsiveness to non-technical signals.

Third, the model's architecture and hyperparameters were fixed to a single configuration (64 LSTM units, 0.005 learning rate, 0.2 dropout). While this configuration yielded strong results, it is not necessarily optimal. Future research could employ grid search or Bayesian optimization techniques to systematically explore alternative hyperparameter combinations, potentially leading to further performance gains.

Moreover, while LSTM was chosen for its strength in capturing long-term dependencies, other deep learning architectures could offer complementary or superior capabilities. Gated Recurrent Units (GRUs), for instance, offer a simpler alternative to LSTM with fewer parameters and comparable performance. Bidirectional LSTM (Bi-LSTM) models can learn from both past and future contexts, potentially improving performance during trend reversals. Transformer-based models—such as the Temporal Fusion Transformer (TFT) or Informer—have also demonstrated state-of-the-art results in time-series prediction tasks and may outperform RNN-based architectures in scenarios requiring long-horizon forecasting [25].

This study confirms the effectiveness of the LSTM model in modeling sequential financial data, particularly when supported by diversified and high-quality data inputs. The integration of multi-source data not only improved accuracy but also enhanced the model's robustness and generalization across two of the most prominent cryptocurrencies. However, the limitations observed during volatile periods, the exclusion of external indicators, and the fixed architecture highlight clear paths for future improvement. As cryptocurrency markets continue to evolve in complexity and scale, forecasting models must likewise evolve to incorporate richer data, adaptive architectures, and real-time context awareness.

4. CONCLUSION

This study successfully developed and evaluated an LSTM-based deep learning model for forecasting the daily closing prices of two leading cryptocurrencies—Bitcoin and Ethereum—using multi-source data from Yahoo Finance and Binance. The experimental results demonstrated that model accuracy and robustness significantly improved when trained on combined datasets, confirming the value of data diversity in time-series forecasting. The model achieved its best performance with a 90:10 train-test split, underscoring the importance of larger training volumes in enhancing generalization. Comparative analysis further

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revealed that Bitcoin, due to its relative price stability and liquidity, was more predictable than Ethereum. While the LSTM model proved effective in capturing temporal patterns, its performance was somewhat challenged during periods of extreme market volatility. The practical deployment of the model via a Streamlit-based web application demonstrated real-world usability, providing an interactive platform for live predictions and financial insights.

REFERENCES

[1] M. F. Rizkilloh and S. Widiyanesti, "Prediksi Harga Cryptocurrency Menggunakan Algoritma Long Short-Term Memory (LSTM)," *J. RESTI (Rekayasa Sist. dan Teknol. Inf.)*, vol. 6, no. 1, pp. 25–31, Feb. 2022, doi: 10.29207/resti.v6i1.3630.
[2] A. Sujjada and F. Sembiring, "Prediksi Harga Bitcoin Menggunakan Algoritma Long Short-Term Memory," *J. Inovtek Polbeng*, vol. 9, pp. 450–459, 2024.
[3] A. Wicaksono, C. E. Violita, and E. R. Kamila, "Bitcoin Sebagai Instrumen Investasi yang Menguntungkan," *Greenomika*, vol. 4, no. 1, pp. 44–49, 2022.
[4] M. W. P. Aldi, J. Jondri, and A. Aditsania, "Analisis dan Implementasi Long Short-Term Memory Neural Network untuk Prediksi Harga Bitcoin," *eProceedings Eng.*, vol. 5, no. 2, 2018.
[5] T. B. Sianturi, I. Cholissodin, and N. Yudistira, "Penerapan Algoritma Long Short-Term Memory (LSTM) Berbasis Multi Fungsi Aktivasi Terbobot dalam Prediksi Harga Ethereum," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 7, no. 3, pp. 1101–1107, 2023.
[6] M. Nirraca and E. Hartati, "Prediksi Harga Bitcoin Menggunakan Metode Long Short-Term Memory," *J. Digit. Teknol. Inf.*, vol. 7, no. 1, pp. 55–65, 2024, doi: 10.32502/digital.v7i1.7974.
[7] I. Indriyanti, N. Ichsan, H. Fatah, T. Wahyuni, and E. Ermawati, "Implementasi Orange Data Mining untuk Prediksi Harga Bitcoin," *J. Responsif: Riset Sains dan Informatika*, vol. 4, no. 2, pp. 118–125, 2022.
[8] R. Faizal, B. D. Setiawan, and I. Cholissodin, "Prediksi Nilai Cryptocurrency Bitcoin Menggunakan Algoritme Extreme Learning Machine (ELM)," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 3, no. 5, pp. 4226–4233, 2019.
[9] M. A. Maliki, I. Cholissodin, and N. Yudistira, "Prediksi Pergerakan Harga Cryptocurrency Bitcoin terhadap Mata Uang Rupiah Menggunakan Algoritme LSTM," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 6, no. 7, pp. 3259–3268, 2022.
[10] A. Santoso, A. I. Purnamasari, and I. Ali, "Prediksi Harga Beras Menggunakan Metode Recurrent Neural Network dan Long Short-Term Memory," *Prosisko J. Pengemb. Ris. dan Obs. Sist. Komput.*, vol. 11, no. 1, pp. 128–136, 2024.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[11] A. Nilsen, "Perbandingan Model RNN, Model LSTM, dan Model GRU dalam Memprediksi Harga Saham-Saham LQ45," *J. Statistika dan Aplikasinya*, vol. 6, no. 1, 2022.
[12] S. A. Tussifah, "Analisis Perbandingan Kinerja Model ARIMA, LSTM dan GRU pada Stock Price Forecasting," B.Sc. thesis, Fak. Sains dan Teknol., Univ. Islam Negeri Syarif Hidayatullah, Jakarta, Indonesia, 2023.
[13] F. Ferdiansyah, S. H. Othman, R. Z. R. M. Radzi, D. Stiawan, Y. Sazaki, and U. Ependi, "A LSTM-Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market," in *Proc. 2019 Int. Conf. Electr. Eng. Comput. Sci. (ICECOS)*, Oct. 2019, pp. 206–210, IEEE.
[14] M. Nirraca and E. Hartati, "Prediksi Harga Bitcoin Menggunakan Metode Long Short-Term Memory," *J. Digit. Teknol. Inf.*, vol. 7, no. 1, pp. 55–65, 2024.
[15] B. Na and G. Fox, "Object Classifications by Image Super-Resolution Preprocessing for Convolutional Neural Networks," *Adv. Sci. Technol. Eng. Syst. J.*, vol. 5, pp. 476–483, Feb. 2020, doi: 10.25046/aj050261.
[16] T. Nurholipah, R. Kurniawan, and Y. A. Wijaya, "Evaluasi Performa Model Regresi Linear dengan RMSE pada Jumlah Penumpang Bus Transjakarta," *JIKA (J. Inform.)*, vol. 8, no. 2, pp. 180–186, 2024.
[17] R. Sari, K. Kusrini, T. Hidayat, and T. Orphanoudakis, "Improved LSTM Method of Predicting Cryptocurrency Price Using Short-Term Data," *IJCCS (Indones. J. Comput. Cybern. Syst.)*, vol. 17, no. 1, pp. 33–42, Feb. 2023, doi: 10.22146/ijccs.80776.
[18] K. Kashif and R. Ślepaczuk, "LSTM-ARIMA as a Hybrid Approach in Algorithmic Investment Strategies," *Knowl.-Based Syst.*, vol. 113563, 2025.
[19] S. Zahara and M. B. Ilmiddafiq, "Prediksi Indeks Harga Konsumen Menggunakan Metode Long Short-Term Memory (LSTM) Berbasis Cloud Computing," *Masa Berlaku Mulai*, vol. 1, no. 3, pp. 357–363, 2017.
[20] R. Cahuantzi, X. Chen, and S. Güttel, "A Comparison of LSTM and GRU Networks for Learning Symbolic Sequences," in *Proc. Sci. Inf. Conf.*, Cham, Switzerland: Springer Nature, Jul. 2023, pp. 771–785, doi: 10.1007/978-3-031-37963-5_53.
[21] A. Baradja and S. Sukoco, "Pemanfaatan Recurrent Neural Network (RNN) untuk Meningkatkan Akurasi Prediksi Mata Uang pada Forex Trading," *J. Softw. Eng. Ampera*, vol. 4, no. 2, pp. 119–131, 2023.
[22] M. Iqbal, M. Iqbal, F. Jaskani, K. Iqbal, and A. Hassan, "Time-Series Prediction of Cryptocurrency Market Using Machine Learning Techniques," *EAI Endorsed Trans. Creative Technol.*, vol. 8, no. 28, p. 170286, Aug. 2021, doi: 10.4108/eai.7-7-2021.170286.
[23] R. Akbar, R. Santoso, and B. Warsito, "Prediksi Tingkat Temperatur Kota Semarang Menggunakan Metode Long Short-Term Memory (LSTM)," *J. Gaussian*, vol. 11, no. 4, pp. 572–579, 2023.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[24] R. Pascanu, T. Mikolov, and Y. Bengio, "On the Difficulty of Training Recurrent Neural Networks," in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2013, pp. 1310–1318, PMLR.
[25] P. Le and W. Zuidema, "Quantifying the Vanishing Gradient and Long-Distance Dependency Problem in Recursive Neural Networks and Recursive LSTMs," *arXiv preprint* arXiv:1603.00423, 2016.