Forecasting Volatile Cryptocurrency Prices: An LSTM Approach Applied to Solana with Advanced Time Series Features

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ABSTRACT

This study aims to develop a deep learning model based on Long Short-Term Memory (LSTM) to forecast Solana cryptocurrency prices using historical time series data. The dataset is enriched with multiple technical indicators, including moving averages, volatility measures, and log return transformation to improve data representation. The model is trained using a sequence length of 30-time steps and evaluated using several performance metrics, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The experimental results show that the proposed model achieves a MAPE value below 5%, indicating high prediction accuracy, and an R^2 value that reflects a strong ability to capture the underlying patterns in the data. The model is able to effectively follow overall price trends and short-term fluctuations, although its performance decreases during periods of high volatility, where sudden price changes occur. These findings suggest that the LSTM model is a suitable approach for modeling non-linear and sequential patterns in cryptocurrency markets, while highlighting the need for further improvements to enhance performance under extreme market conditions.

Keywords LSTM, Cryptocurrency Price Prediction, Time Series Forecasting, Solana (SOL), Deep Learning

INTRODUCTION

Cryptocurrency has become an important component of the modern financial ecosystem, attracting significant attention from investors, researchers, and policymakers. Among the various cryptocurrencies available, Solana (SOL) has gained considerable popularity due to its high transaction throughput, low fees, and rapidly expanding ecosystem. Despite these advantages, Solana price movements are highly volatile and exhibit complex non-linear patterns, making accurate prediction a challenging task. This volatility is influenced by various factors, including market sentiment, technological developments, and macroeconomic conditions, which further complicate the forecasting process [1].

Time series forecasting has been widely used to analyze financial data, including cryptocurrency prices. Traditional statistical models, such as Autoregressive Integrated Moving Average (ARIMA), have been commonly applied for this purpose. However, these models often rely on linear assumptions and are limited in their ability to capture complex and non-linear relationships present in financial time series data. As a result, their performance tends to decrease when dealing with highly dynamic and volatile markets such as cryptocurrencies [2].

Recent advances in deep learning have introduced more powerful approaches

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for time series forecasting. In particular, Long Short-Term Memory (LSTM) networks have emerged as one of the most effective models for sequential data analysis. LSTM is capable of capturing long-term dependencies and learning non-linear patterns, making it suitable for modeling financial time series. Previous studies have shown that LSTM-based models outperform traditional methods in predicting cryptocurrency prices, especially when combined with feature engineering techniques such as technical indicators and data transformations [3], [4].

Despite these advancements, several research gaps remain. First, most existing studies primarily focus on well-established cryptocurrencies such as Bitcoin and Ethereum, while relatively limited research has been conducted on emerging cryptocurrencies like Solana. Second, many studies rely on raw price data without incorporating comprehensive feature engineering, which may limit the model's ability to capture underlying market dynamics. Third, the ability of LSTM models to accurately predict prices during periods of extreme volatility remains limited, as sudden market movements are difficult to model using historical data alone [5].

Therefore, this study aims to develop an LSTM-based deep learning model to forecast Solana cryptocurrency prices using enriched time series data. The proposed approach incorporates multiple technical indicators, including moving averages, volatility measures, and log return transformation, to enhance the representation of the data. In addition, the model is evaluated using multiple performance metrics to provide a comprehensive assessment of its predictive capability. By addressing the identified research gaps and focusing on Solana as a case study, this research contributes to the development of more robust and accurate models for cryptocurrency price prediction.

Literature Review and Related Works

Time series forecasting has been widely applied in financial markets to predict asset prices, including cryptocurrencies. Traditional statistical approaches such as Autoregressive Integrated Moving Average (ARIMA) have been commonly used due to their simplicity and interpretability. However, these models assume linear relationships and often fail to capture the complex and non-linear behavior of cryptocurrency price movements [6], [7]. As a result, their performance is generally limited when applied to highly volatile and dynamic financial data.

With the advancement of machine learning, more sophisticated models have been introduced to address these limitations. Techniques such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) have been applied to financial time series forecasting and have shown improved performance compared to traditional models [8], [9]. Nevertheless, these models still face challenges in handling sequential dependencies effectively, as they are not specifically designed for time series data with temporal structures.

Deep learning approaches, particularly Recurrent Neural Networks (RNN), have gained significant attention due to their ability to process sequential data. Among these, Long Short-Term Memory (LSTM) networks have emerged as one of the most effective models for time series forecasting [10], [11]. LSTM is designed to overcome the vanishing gradient problem and is capable of learning long-term dependencies, making it suitable for modeling financial time series with complex patterns [12]. Several studies have demonstrated that LSTM

outperforms traditional models in predicting stock and cryptocurrency prices [13], [14].

In the context of cryptocurrency forecasting, many studies have focused on major assets such as Bitcoin and Ethereum. These studies have shown that LSTM models can effectively capture non-linear price dynamics and provide more accurate predictions compared to conventional approaches [15], [16]. In addition, the integration of feature engineering techniques, such as technical indicators and data transformations, has been found to significantly improve model performance by providing more informative input features [17], [18].

Despite these advancements, several challenges remain in the field. First, limited research has been conducted on emerging cryptocurrencies such as Solana, which may exhibit different market characteristics compared to more established assets [19]. Second, many existing studies rely primarily on historical price data without incorporating a comprehensive set of features, which may limit the model's predictive capability [17]. Third, accurately modeling extreme volatility and sudden market changes remains a significant challenge for deep learning models, including LSTM [20]. Therefore, further research is needed to develop more robust and adaptive models that can better handle the dynamic nature of cryptocurrency markets.

Methodology

Research Framework

This study follows a structured methodology to develop and evaluate an LSTM-based model for forecasting Solana cryptocurrency prices. The overall research workflow is illustrated in figure 1, which consists of several main stages, including data collection, data preprocessing, feature engineering, data normalization, sequence generation, model development, training, and evaluation. This systematic approach ensures that each stage contributes to improving the model's ability to capture temporal patterns and produce accurate predictions.

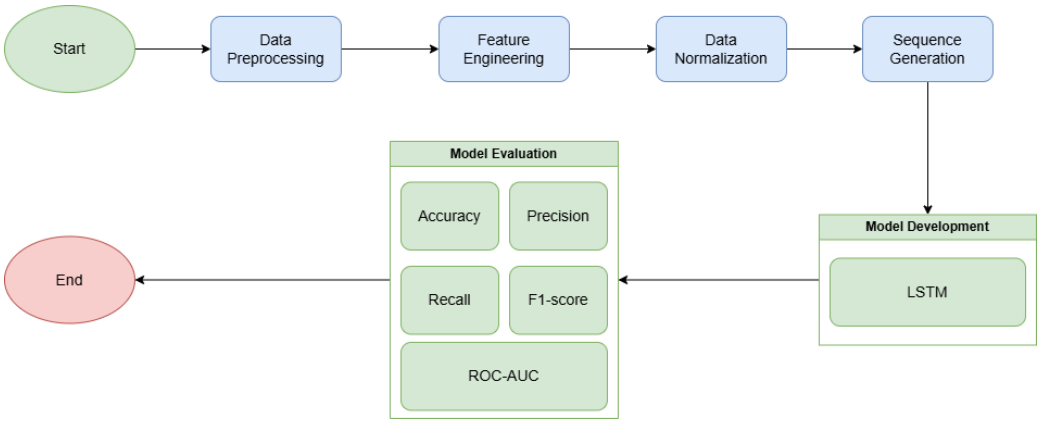


Figure 1 Research Steps

Data Collection

The dataset used in this study consists of historical price data of Solana (SOL), including attributes such as Date, Open, High, Low, Price, Volume, and percentage change. The data is arranged chronologically to maintain the time

series structure required for sequential modeling.

Data Preprocessing

The preprocessing stage includes converting the date into a standard datetime format and transforming the trading volume into numerical values. The percentage change is also cleaned and converted into a numerical format. Missing values resulting from transformation are removed to ensure data consistency.

Feature Engineering

Several additional features are generated to enhance the model's learning capability. The daily return is calculated as:

$$Return_t = \frac{Price_t - Price_{t-1}}{Price_{t-1}} \tag{1}$$

The log return is computed to stabilize variance:

$$LogReturn_t = \ln\left(\frac{Price_t}{Price_{t-1}}\right) \tag{2}$$

Moving averages are calculated to capture trend information:

$$MA_n = \frac{1}{n}\sum_{i=0}^{n-1} Pric\, e_{t-i} \tag{3}$$

Volatility is represented using rolling standard deviation:

$$STD_n = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(Pric\, e_{t-i} - MA_n)^2} \tag{4}$$

Additional features include high-low range and open-close difference:

$$\begin{aligned} HL_Range &= High - Low \\ OC_Diff &= Open - Price \end{aligned} \tag{5}$$

Data Normalization and Splitting

The dataset is divided into training and testing sets using an 80:20 ratio. MinMax normalization is applied as follows:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

This transformation scales all features into a range between 0 and 1, improving model convergence.

Sequence Generation

To prepare the data for LSTM, a sliding window approach is used. Each

sequence consists of 30 time steps:

$$X_t = [x_{t-30}, x_{t-29}, \ldots, x_{t-1}]$$
$$y_t = LogReturn_t \quad (7)$$

This allows the model to learn temporal dependencies from past observations.

Model Architecture

The model uses a stacked LSTM architecture. The LSTM cell operates based on the following equations:

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (8)$$

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (9)$$

Candidate memory:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (10)$$

Cell state update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (11)$$

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (12)$$

Hidden state:

$$h_t = o_t \cdot \tanh(C_t) \quad (13)$$

The architecture consists of two LSTM layers with 64 and 32 units, followed by dropout layers and dense layers for final prediction.

Model Training

The model is trained using the Adam optimizer with learning rate 0.0005 and mean squared error as the loss function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (14)$$

Early stopping and learning rate reduction are applied to improve training stability and prevent overfitting.

Prediction and Reconstruction

The predicted log return is converted back to price using:

$$Price_t = Price_{t-1} \times e^{LogReturn_t} \tag{15}$$

This allows the model to produce interpretable price predictions.

Model Evaluation

The model is evaluated using several metrics:

Root Mean Squared Error:

$$RMSE = \sqrt{\frac{1}{n}\sum(y - \hat{y})^2} \tag{16}$$

Mean Absolute Error:

$$MAE = \frac{1}{n}\sum | y - \hat{y} | \tag{17}$$

Mean Absolute Percentage Error:

$$MAPE = \frac{100}{n}\sum \left| \frac{y - \hat{y}}{y} \right| \tag{18}$$

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum(y - \hat{y})^2}{\sum(y - \bar{y})^2} \tag{19}$$

Algorithm 1 LSTM-Based Solana Price Forecasting

Input: dataset D, time step $T = 30$

Output: predicted price $\hat{P}_t$

Process:

Start

Load dataset $D$and sort by date

Convert volume and percentage change into numerical values

Remove missing data

for each time step t:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

$$LR_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

$$MA_n = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}$$

$$STD_n = \sqrt{\frac{1}{n}\sum(P_{t-i} - MA_n)^2}$$

$$HL_t = High_t - Low_t$$

$$OC_t = Open_t - P_t$$

end

Define feature matrix $X$and target $y = LR$

Split data into training and testing sets

Normalize data using MinMaxScaler

for each sequence:

$$X_t = [x_{t-T}, \ldots, x_{t-1}]$$
$$y_t = LR_t$$

end

Build LSTM model:

LSTM (64) → Dropout → LSTM (32) → Dense → Output

Train model using Adam optimizer and MSE loss

Predict log return:

$$\widehat{LR}_t = model(X_t)$$

Convert to price:

$$\hat{P}_t = P_{t-1} \times e^{\widehat{LR}_t}$$

Evaluate model:

$$RMSE = \sqrt{\frac{1}{n}\sum(P_t - \hat{P}_t)^2}$$
$$MAE = \frac{1}{n}\sum | P_t - \hat{P}_t |$$
$$MAPE = \frac{100}{n}\sum | \frac{P_t - \hat{P}_t}{P_t} |$$

End

Results

Training Performance

The LSTM model was trained using historical Solana price data with a sequence length of 30 time steps, meaning that each prediction is based on the previous 30 observations. During the training process, the model exhibits a rapid reduction in loss values in the initial epochs, indicating that it quickly learns the underlying patterns in the data. As training progresses, the decrease in loss becomes more gradual, suggesting that the model is approaching convergence. This behavior reflects an effective learning process in which the model captures both short-term and long-term dependencies present in the time series data.

The training performance is illustrated in figure 2, where the training loss decreases significantly from approximately 0.138 to around 0.01, while the validation loss stabilizes within the range of 0.005 to 0.007. The relatively small difference between training and validation loss indicates that the model maintains good generalization capability when applied to unseen data. In addition, the stability of the validation loss over epochs suggests that the implemented regularization techniques, such as dropout and early stopping, are effective in preventing overfitting. This result demonstrates that the model achieves a balanced performance between fitting the training data and maintaining predictive reliability on the validation set.

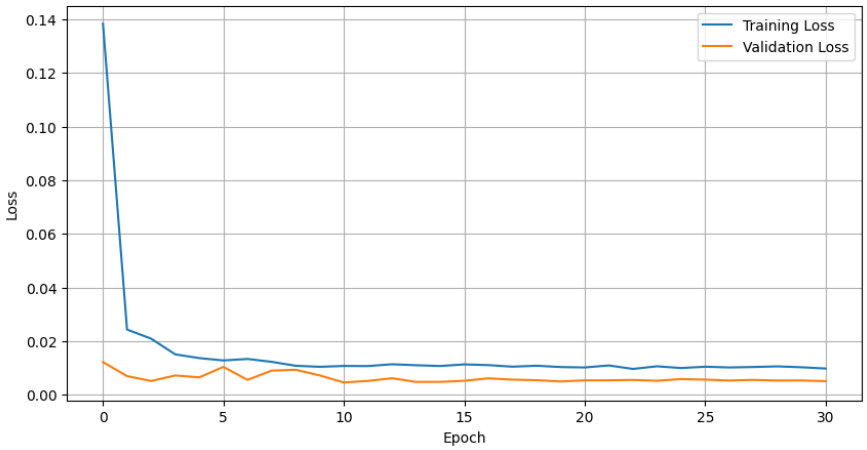


Figure 2 Training and Validation Loss Curve

Prediction Accuracy

The performance of the LSTM model was evaluated using multiple metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2), as presented in table 1. The obtained RMSE value of 1.188 and MAE of 0.880 indicate that the average deviation between predicted and actual prices is relatively small in absolute terms, reflecting good numerical accuracy of the model. Furthermore, the MAPE value of 3.94% suggests that the model achieves high predictive accuracy, as the average percentage error remains below 5%, which is generally considered acceptable for financial time series forecasting. In addition, the R^2 value of 0.601 indicates that approximately 60% of the variance in Solana price movements can be explained by the model, demonstrating a moderate to strong explanatory capability. Overall, these results confirm that the LSTM model is effective in capturing the underlying patterns of the data, although some variability in price movements remains unexplained due to the inherently volatile nature of cryptocurrency markets.

Table 1 Performance Evaluation Metrics

Metric	Value
RMSE	1.188
MAE	0.880
MAPE	3.94%
R^2	0.601

Actual vs Predicted Price

The comparison between actual and predicted prices is presented in figure 3, which demonstrates that the LSTM model is capable of following the overall movement pattern of Solana prices over time. The predicted curve closely tracks the direction of the actual price series, indicating that the model successfully learns the underlying temporal structure of the data. In particular, the model is able to capture general trends such as upward and downward movements, suggesting that the extracted features and sequence modeling approach are effective in representing the dynamics of the cryptocurrency market.

Furthermore, the alignment between predicted and actual values is more consistent during periods of relatively stable market conditions, where price changes occur gradually. The model also shows the ability to reflect short term fluctuations, although with some degree of smoothing. However, noticeable deviations appear during periods of rapid price changes, where the predicted values tend to lag behind the actual movements or underestimate extreme values. This behavior indicates that while the model performs well in capturing general trends, it has limitations in responding to sudden and highly volatile market conditions, which are common in cryptocurrency price movements.

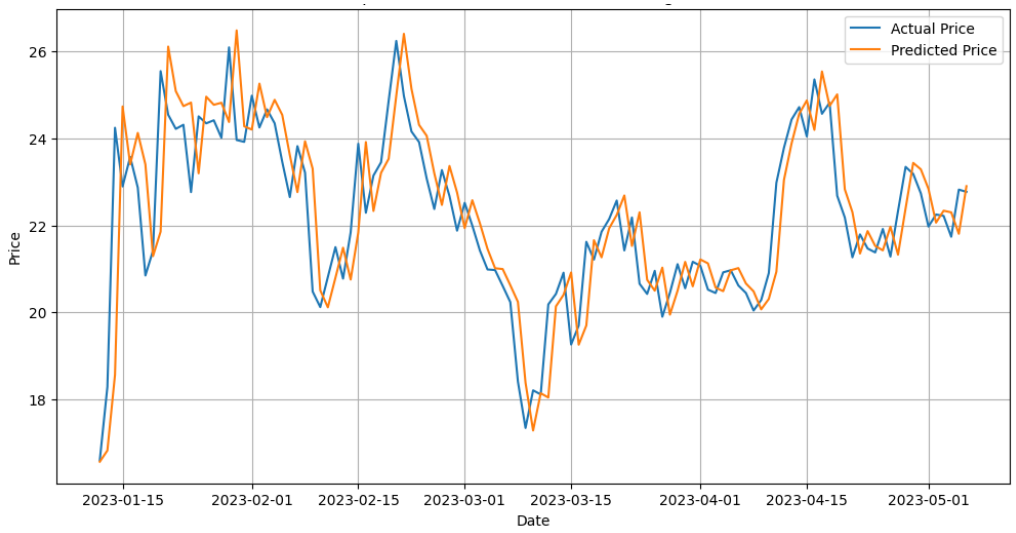


Figure 3 Actual vs Predicted Solana Price

Short-Term Prediction Analysis

A zoomed-in visualization of the last 100 data points is presented in figure 4, providing a more detailed view of the model's performance in capturing short-term price dynamics. The figure shows that the predicted values consistently remain close to the actual prices, indicating that the model effectively leverages recent historical information within the 30 time step window to generate accurate forecasts. The model is able to follow small fluctuations and short-term trends with relatively high precision, which demonstrates its strength in modeling local temporal dependencies. However, minor lag effects are still observable when sudden price spikes or sharp declines occur, where the predicted values tend to respond slightly slower than the actual movements. This suggests that while the model performs well under normal market conditions, its responsiveness to abrupt changes is somewhat limited, reflecting the inherent difficulty of predicting highly volatile behavior in cryptocurrency markets.

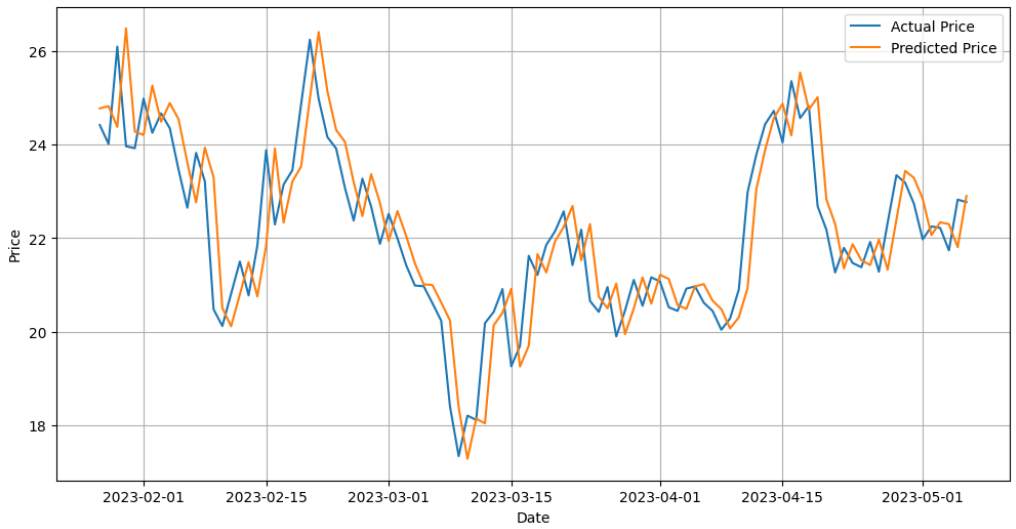


Figure 4 Zoomed Prediction (Last 100 Data Points)

Error Analysis

The prediction error over time is illustrated in figure 5, which provides insight into how the model's accuracy varies across different periods. The majority of the prediction errors are concentrated within the range of -2 to +2, indicating that the model is generally able to produce predictions with relatively small deviations from the actual values. This consistent clustering of errors around zero suggests that the model does not exhibit systematic bias, as it does not consistently overestimate or underestimate the price. Instead, the errors fluctuate symmetrically, reflecting stable predictive behavior under normal market conditions.

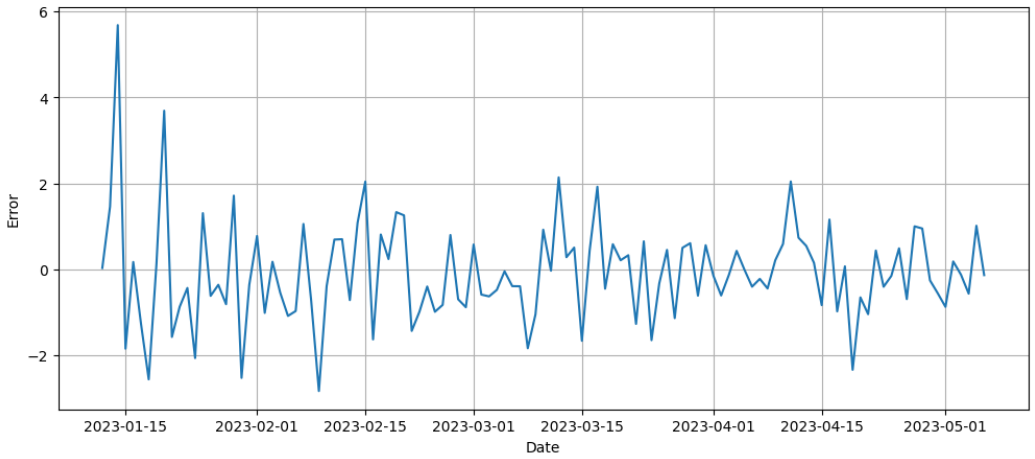


Figure 5 Prediction Error

However, several outliers with larger errors, reaching up to approximately ±5, can be observed at certain points in time. These larger deviations typically occur during periods of heightened market volatility, where rapid and unpredictable price movements take place. In such situations, the model tends to struggle in accurately capturing sudden changes, leading to increased prediction errors. This limitation highlights the inherent challenge of modeling highly volatile

financial time series and suggests that while the LSTM model performs well under stable conditions, its ability to respond to extreme fluctuations remains constrained.

Correlation Analysis

The relationship between actual and predicted prices is illustrated in figure 6, which provides a visual assessment of the model's predictive accuracy through a scatter plot representation. The majority of data points are distributed closely along the diagonal line, indicating a strong positive correlation between actual and predicted values.

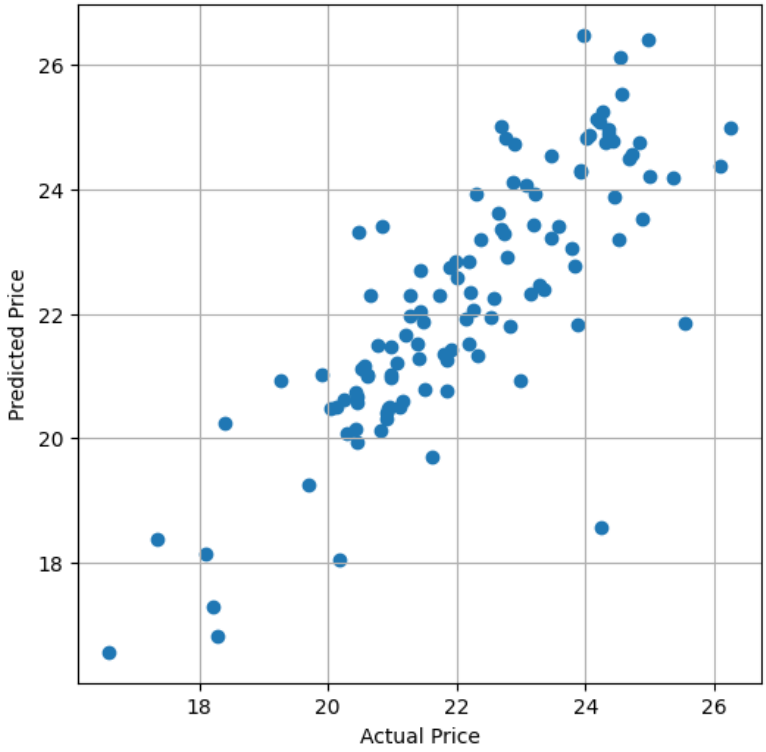


Figure 6 Actual vs Predicted Scatter Plot

This alignment suggests that the model is generally successful in estimating price levels with a high degree of accuracy across most observations. The concentration of points around the diagonal also implies that the prediction errors are relatively small for a large portion of the dataset, reinforcing the effectiveness of the LSTM model in capturing the overall structure of the data. However, a wider dispersion of points is observed at higher price levels, indicating that the model exhibits reduced precision when predicting more extreme values. This pattern suggests that while the model performs reliably under typical conditions, its accuracy decreases as price volatility increases, particularly in regions where the data exhibits larger fluctuations.

Discussion

The results obtained from this study indicate that the LSTM model provides a reliable approach for forecasting Solana cryptocurrency prices, particularly in capturing underlying trends and short-term temporal dependencies in time-series data [21]. The relatively low values of RMSE, MAE, and MAPE

demonstrate that the model produces predictions with small deviations from actual values, reflecting strong numerical accuracy. A MAPE value below 5% further indicates a high level of predictive accuracy for the evaluated dataset, although its practical acceptability depends on the forecasting context and evaluation methodology [22]. In addition, the R^2 value suggests that the model can explain a substantial portion of the variability in price movements, indicating that the extracted features and sequential learning process effectively represent the underlying data patterns. The application of log-return transformation and multiple technical indicators may also improve model performance by reducing scale-related effects and enriching the input features used for prediction [23].

Despite these strengths, the model exhibits certain limitations, particularly during periods of high market volatility. The analysis of prediction errors and visualizations indicates that the model tends to produce less accurate predictions when sudden price spikes or sharp declines occur. In such situations, the model may respond with a slight delay or underestimate extreme values, indicating limited sensitivity to abrupt market changes [24]. This limitation may be associated with the absence of external influencing factors, such as market sentiment, macroeconomic conditions, and unexpected news events, which can significantly affect cryptocurrency price movements. Furthermore, the wider dispersion observed at higher price levels suggests that prediction errors may increase when the model encounters extreme values, highlighting the challenges of forecasting highly volatile financial time series. Therefore, although the LSTM model demonstrates strong overall performance, further improvements are needed to enhance its robustness under dynamic and unpredictable market conditions.

Conclusion

This study developed an LSTM-based deep learning model to forecast Solana cryptocurrency prices using historical time series data enriched with multiple technical indicators and log return transformation. The experimental results demonstrate that the model is capable of capturing both trend patterns and short-term fluctuations with a relatively high level of accuracy, as indicated by low RMSE, MAE, and a MAPE value below 5%, which is considered acceptable for financial forecasting tasks. In addition, the R^2 value shows that the model is able to explain a significant portion of the variance in price movements, confirming its effectiveness in learning the underlying structure of the data. However, the model exhibits limitations when dealing with highly volatile conditions, where sudden price spikes or sharp declines lead to increased prediction errors and slight lag in response. This indicates that while the model performs well under normal market conditions, its ability to generalize to extreme events is still limited. Overall, the findings suggest that LSTM is a suitable approach for cryptocurrency price prediction, but further improvements, such as incorporating external factors or combining multiple models, are necessary to enhance performance in highly dynamic and unpredictable market environments.

Declarations

Author Contributions

Conceptualization: C.I.S.N.; Methodology: C.I.S.N., E.I.; Software: E.I.; Validation: C.I.S.N., E.I.; Formal Analysis: C.I.S.N.; Investigation: C.I.S.N., E.I.; Resources: E.I.; Data Curation: C.I.S.N.; Writing – Original Draft Preparation: C.I.S.N.; Writing – Review and Editing: C.I.S.N., E.I.; Visualization: E.I.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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