Comparative Analysis of Machine Learning and LSTM Models for Solana Price Prediction Using Technical Indicators

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ABSTRACT

This study proposes a predictive framework for forecasting Solana cryptocurrency prices using a Long Short-Term Memory (LSTM) model and compares its performance with several machine learning approaches, including Linear Regression, Ridge Regression, Random Forest, Extra Trees, and Gradient Boosting. Historical price data were enhanced with technical indicators such as moving averages, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) to improve feature representation. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The results show that Linear Regression achieved the best overall performance, producing the lowest error values and highest R^2 score, while the LSTM model exhibited the lowest predictive accuracy. These findings indicate that simpler machine learning models can outperform deep learning approaches when the dataset is limited and the features are highly informative. Furthermore, feature importance analysis reveals that fundamental price variables such as Close, Open, High, and Low contribute more significantly to prediction performance than complex technical indicators. Overall, the study highlights the importance of aligning model complexity with data characteristics and demonstrates that effective feature engineering plays a critical role in improving cryptocurrency price prediction accuracy.

Keywords Cryptocurrency Price Prediction, Long Short-Term Memory (LSTM), Machine Learning Comparison, Technical Indicators, Time Series Forecasting

INTRODUCTION

Cryptocurrency has become an increasingly important component of the global financial landscape, driven by rapid technological advancements and growing interest in decentralized digital assets [1]. Unlike traditional financial markets, cryptocurrency markets operate continuously and are highly sensitive to market sentiment, technological developments, and macroeconomic factors. Among the various cryptocurrencies, Solana has emerged as a prominent platform due to its high throughput, low transaction costs, and scalability. Despite its advantages, the price behavior of Solana remains highly volatile and exhibits complex patterns, making accurate prediction a challenging task for researchers and practitioners [2].

The inherent characteristics of cryptocurrency time series data, including non-stationarity, noise, and nonlinear dependencies, require robust modeling approaches that can effectively capture both temporal dynamics and structural relationships. Traditional statistical methods often struggle to model such complexities, leading to the adoption of machine learning techniques. Models

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such as Linear Regression, Random Forest, and Gradient Boosting have been widely applied due to their ability to model relationships between input features and target variables. These models are particularly effective when the data has been transformed through feature engineering, which enhances the representation of underlying patterns [3].

In recent years, deep learning approaches have gained significant attention in financial time series forecasting, particularly Long Short-Term Memory networks, which are designed to capture long-term dependencies in sequential data. LSTM models have been successfully applied in various domains, including stock price prediction and cryptocurrency forecasting, where they are often reported to outperform traditional machine learning methods [4]. The ability of LSTM to learn complex nonlinear relationships and temporal patterns makes it a strong candidate for modeling highly dynamic markets such as cryptocurrencies.

However, despite the growing adoption of deep learning models, several research gaps remain. Many existing studies focus primarily on a single modeling approach, either machine learning or deep learning, without conducting a comprehensive comparison under consistent experimental conditions. In addition, while technical indicators such as Moving Average, Relative Strength Index, and Moving Average Convergence Divergence are frequently incorporated into prediction models, their relative importance and contribution to model performance are not always thoroughly analyzed. Furthermore, the relationship between feature engineering and model complexity is often overlooked, particularly in scenarios where engineered features may already capture significant temporal information, potentially reducing the need for complex sequence-based models [5].

To address these limitations, this study proposes a comprehensive comparative framework for predicting Solana cryptocurrency prices by integrating feature engineering with both machine learning and deep learning approaches. Specifically, a Long Short-Term Memory model is developed and compared with several machine learning models, including Linear Regression, Ridge Regression, Random Forest, Extra Trees, and Gradient Boosting. The models are evaluated using multiple performance metrics to ensure a robust and fair comparison. The main contribution of this study is to provide empirical insights into the effectiveness of different modeling approaches in relation to data characteristics and feature representation, as well as to examine whether complex deep learning models consistently outperform simpler machine learning methods in cryptocurrency price prediction tasks.

Literature Review and Related Works

Cryptocurrency price prediction has become an active area of research due to the increasing adoption of digital assets and their highly volatile nature. Early approaches focused on statistical and econometric models; however, these methods often fail to capture the nonlinear and dynamic behavior of cryptocurrency markets [6], [7]. As a result, machine learning techniques have been widely adopted to improve prediction performance by modeling complex relationships between variables.

Traditional machine learning models such as Linear Regression, Support Vector Machines, and ensemble methods including Random Forest and

Gradient Boosting have been extensively applied in financial forecasting tasks [8], [9], [10]. These models are effective in handling structured data and can provide reliable predictions when combined with appropriate feature engineering techniques. In the context of cryptocurrency markets, several studies have demonstrated that machine learning models can achieve competitive performance, particularly when incorporating historical price data and derived features [11], [12].

With the advancement of deep learning, neural network-based models have gained significant attention for time series forecasting. Among these, Long Short-Term Memory networks are widely used due to their ability to capture long-term dependencies and sequential patterns in temporal data [13], [14]. LSTM models have been successfully applied to stock and cryptocurrency price prediction, where they are often reported to outperform traditional machine learning approaches in capturing nonlinear dynamics [15], [16]. Variants such as Bidirectional LSTM and hybrid deep learning models have also been proposed to further enhance prediction accuracy [17], [18].

In addition to model selection, feature engineering plays a crucial role in improving prediction performance. Technical indicators such as Moving Average, Relative Strength Index, and Moving Average Convergence Divergence are commonly used to extract meaningful patterns from raw price data [19], [20]. These indicators help transform time series data into a structured format, making it more suitable for machine learning models. However, the effectiveness of these indicators may vary depending on the dataset and the modeling approach.

Despite the growing body of research, several limitations remain. Many studies focus on a single category of models without conducting a comprehensive comparison between machine learning and deep learning approaches under the same experimental setup. Furthermore, the combined effect of feature engineering and model complexity is not always thoroughly investigated. Therefore, a systematic comparison of different models using consistent data preprocessing and feature engineering techniques is necessary to better understand their relative performance in cryptocurrency price prediction tasks.

Methodology

Research Framework and Dataset

This study follows a structured research framework that includes data collection, preprocessing, feature engineering, model development, and evaluation. The overall workflow of the proposed methodology is illustrated in figure 1, which presents the sequence of steps from raw data processing to model comparison and performance evaluation. The dataset used in this study consists of historical daily price data of the Solana cryptocurrency, including Open, High, Low, Close prices, trading Volume, and percentage Change. The dataset initially contains 999 observations and spans multiple market conditions. After preprocessing and feature engineering, 969 valid observations were retained for further analysis. The data was sorted chronologically to preserve temporal dependencies, which is essential for time series modeling.

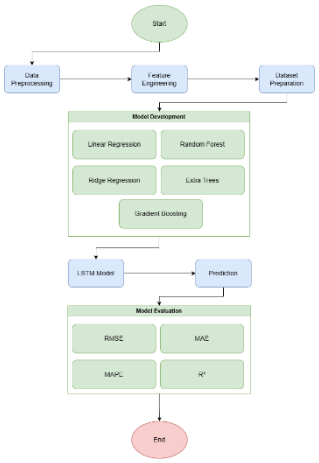


Figure 1 Research Framework

Data Preprocessing

Data preprocessing was performed to ensure consistency and reliability. String-based numerical values were converted into floating-point format, and volume values expressed in abbreviated units were normalized. Missing values were handled using forward fill and backward fill methods. The dataset was then cleaned to remove invalid entries and sorted based on date to maintain temporal order.

Feature Engineering

Feature engineering was applied to extract meaningful information from raw data. Several statistical and technical indicators were calculated as follows:

Return:

$$Return_t = \frac{Close_t - Close_{t-1}}{Close_{t-1}} \quad (1)$$

Log Return:

$$LogReturn_t = \ln\left(\frac{Close_t}{Close_{t-1}}\right) \quad (2)$$

Price Difference:

$$PriceDiff_t = Close_t - Close_{t-1} \quad (3)$$

Moving Average (MA):

$$MA_n = \frac{1}{n}\sum_{i=0}^{n-1} Clos\, e_{t-i} \quad (4)$$

Standard Devation:

$$STD_n = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(Clos\, e_{t-i} - \bar{Close})^2} \quad (5)$$

Volatility:

$$Volatility_n = STD(Return_{t-n:t}) \quad (6)$$

Relative Strength Index (RSI):

$$RSI = 100 - \frac{100}{1+RS}$$
$$RS = \frac{Average\ Gain}{Average\ Loss} \quad (7)$$

MACD:

$$MACD = EMA_{12} - EMA_{26} \quad (8)$$

Signal Line:

$$Signal = EMA_9(MACD) \quad (9)$$

The target variable is defined as:

$$Target = Close_{t+1} \quad (10)$$

These features enable the model to capture trend, momentum, and volatility characteristics of the market.

Data Splitting and Normalization

The dataset was divided into training and testing sets using an 80:20 ratio while preserving chronological order. Feature scaling was performed using Min-Max normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (11)$$

This ensures that all input features are within a comparable range, which is particularly important for neural network training.

Machine Learning Models

The machine learning models used in this study for comparative analysis include Linear Regression, Ridge Regression, Random Forest, Extra Trees, and Gradient Boosting. These models were selected to represent both linear and nonlinear learning approaches, providing a comprehensive evaluation across different modeling paradigms. Linear Regression and Ridge Regression are employed to capture linear relationships between input features and the target variable, while ensemble-based models such as Random Forest, Extra Trees, and Gradient Boosting are designed to model more complex and nonlinear interactions. All models were trained using the normalized dataset to ensure consistency and to improve learning stability. The performance of each model was then evaluated based on its ability to accurately capture patterns and relationships within the data.

LSTM Model Development

To model temporal dependencies, the dataset was transformed into sequences using a sliding window approach:

$$X_t = [x_{t-n}, \ldots, x_{t-1}] \quad (12)$$

$n = 60$represents the sequence length.

The LSTM model consists of two stacked LSTM layers with 128 and 64 units, followed by dropout layers to reduce overfitting. A dense layer is used before the output layer to improve learning capacity. The model is trained using the Adam optimizer with mean squared error as the loss function.

Model Evaluation

Model performance was evaluated using the following metrics:

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (13)$$

Mean Absolute Error (MAE):

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

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} | \quad (15)$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (16)$$

These metrics provide a comprehensive evaluation of prediction accuracy and model performance.

Algorithm 1: Solana Price Prediction using LSTM and Machine Learning

Input: historical dataset D(Open, High, Low, Close, Volume, Change)
Output: predicted closing price $\hat{y}_{t+1}$and evaluation metrics
Process:
Start
Data Preprocessing
Convert all numerical values into floating-point format
Handle missing values using forward fill and backward fill
Sort dataset based on chronological order
Feature Engineering
Compute return:
$return = \frac{Close_t - Close_{t-1}}{Close_{t-1}}$
Compute log return:
$log_return = \ln\left(\frac{Close_t}{Close_{t-1}}\right)$
Compute moving average:
$MA_n = \frac{1}{n}\sum Close$
Compute RSI and MACD indicators
Define target variable:

$y = Close_{t+1}$

Data Splitting and Scaling

Split dataset into training and testing sets (80:20)

Normalize data using Min-Max scaling

Machine Learning Models

For each model in {Linear Regression, Ridge, Random Forest, Extra Trees, Gradient Boosting}:

Train model using training data

Predict output on testing data

Store prediction results

LSTM Model

Create sequence data with window size = 60

Define LSTM architecture:

LSTM (128) → Dropout → LSTM (64) → Dense → Output

Train model using training sequences

Predict output using testing sequences

Evaluation

Compute RMSE, MAE, MAPE, and R^2:

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

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

$MAPE = \frac{100}{n}\sum | \frac{y-\hat{y}}{y} |$

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

Select best model based on evaluation metrics

End

Results

Data Characteristics

The Solana price dataset demonstrates pronounced volatility and clear non-stationary behavior throughout the observation period, with substantial fluctuations in price levels over time. A strong upward trend is evident during 2021, where prices increased rapidly, indicating a bullish market phase, followed by a sharp and sustained decline in 2022 that reflects a bearish correction. In 2023, the price movement appears relatively more stable, with smaller fluctuations compared to previous periods, suggesting a consolidation phase. As shown in figure 2, the overall price trajectory highlights these distinct market cycles and major fluctuations. Additionally, the moving average indicators, including MA 7, MA 14, and MA 30, effectively smooth short-term noise in the data and provide clearer visualization of underlying trends, with shorter windows capturing immediate price movements and longer windows reflecting broader trend directions.

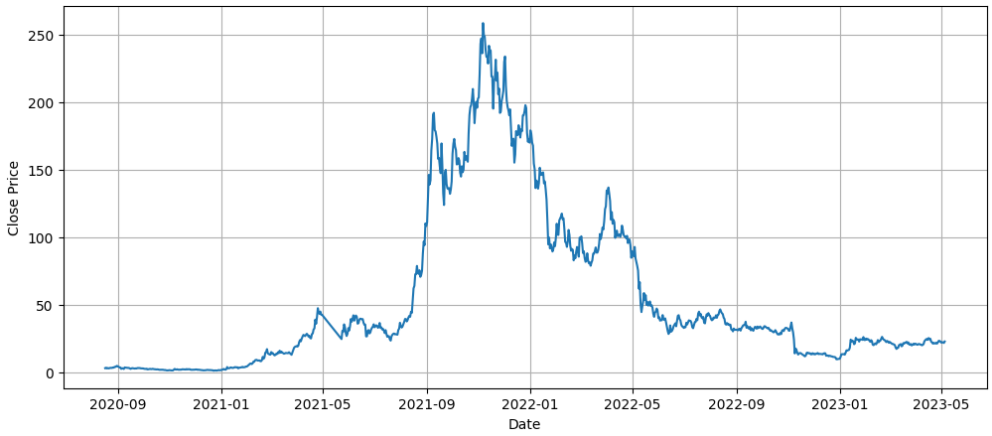


Figure 2 Solana Closing Price Over Time

Model Performance Evaluation

The performance of all models was evaluated using four standard metrics, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2), to provide a comprehensive assessment of prediction accuracy and error distribution. RMSE and MAE measure the magnitude of prediction errors, with lower values indicating better performance, while MAPE provides a relative error percentage that is useful for interpretability. The R^2 metric reflects how well the model explains the variance in the actual data. The evaluation results presented in table 1 show clear differences in model performance across these metrics.

Among all evaluated models, Linear Regression achieved the best overall performance, with the lowest RMSE, MAE, and MAPE values, as well as the highest R^2 score, indicating a strong fit to the observed data and high predictive accuracy. Ridge Regression also performed competitively, although slightly below Linear Regression across all metrics. In contrast, the LSTM model produced the highest error values and the lowest R^2 score, indicating significantly lower predictive accuracy compared to the other models. This performance gap highlights the differences in how each model captures patterns in the data under the given experimental setup.

Table 1 Model Performance Comparison

Model	RMSE	MAE	MAPE (%)	R^2
Linear Regression	1.4937	0.9400	4.8295	0.9301
Ridge Regression	1.6183	1.0327	5.3305	0.9180
Extra Trees	2.9794	2.5222	13.7484	0.7220
Gradient Boosting	3.1924	2.6409	14.4679	0.6808
Random Forest	3.3027	2.7776	15.8728	0.6583
LSTM	4.3298	3.0890	18.8885	0.1887

Prediction Results

The comparison between actual and predicted values provides insight into each model's ability to follow the underlying price dynamics and capture fluctuations in the Solana market. As shown in figure 3, the LSTM model generates predictions that generally follow the overall direction of the price trend but exhibit

a noticeably smoother pattern compared to the actual values. While the model is able to approximate the general movement of the series, it fails to accurately track sudden increases and sharp declines in price. This smoothing effect indicates that the LSTM model tends to underreact to rapid market changes, resulting in larger deviations during highly volatile periods and contributing to reduced prediction accuracy.



Figure 3 Actual vs LSTM Predicted Prices

In contrast, the machine learning models demonstrate a closer alignment with the actual price movements, indicating a stronger ability to capture both the overall trend and short-term variations in the data. As illustrated in figure 4, the predicted values from models such as Linear Regression, Ridge Regression, and ensemble methods generally follow the actual price trajectory with smaller deviations compared to the LSTM model. The prediction curves show a higher responsiveness to changes in price direction, including moderate fluctuations, which results in improved tracking of the underlying pattern. Although some deviations are still present during periods of high volatility, the overall consistency between predicted and actual values suggests that these models are more effective in modeling the relationship between input features and the target variable under the given experimental conditions.

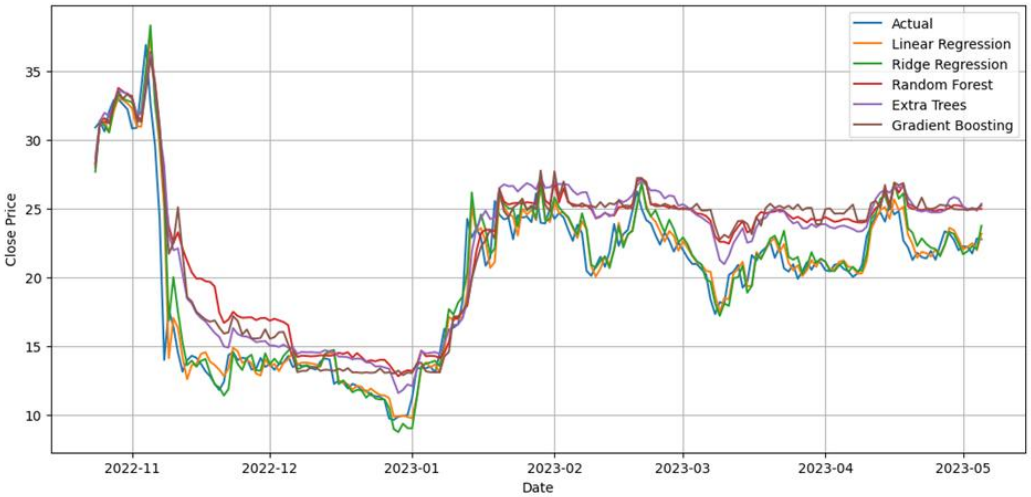


Figure 4 Machine Learning Models vs Actual Prices

LSTM Training Performance

The training and validation loss curves of the LSTM model, as shown in figure 5, demonstrate a steady reduction in error throughout the training process, indicating that the model is effectively learning patterns from the data. During the initial epochs, both training and validation losses decrease rapidly, reflecting significant improvements in model performance. As training progresses, the rate of decrease becomes more gradual, and both curves begin to stabilize, suggesting that the model is approaching convergence. The relatively close alignment between training and validation loss indicates that the model does not exhibit severe overfitting, although minor fluctuations may still occur. Overall, the loss trends confirm that the training process is stable and that the model has reached a point were further training yields minimal improvement in performance.

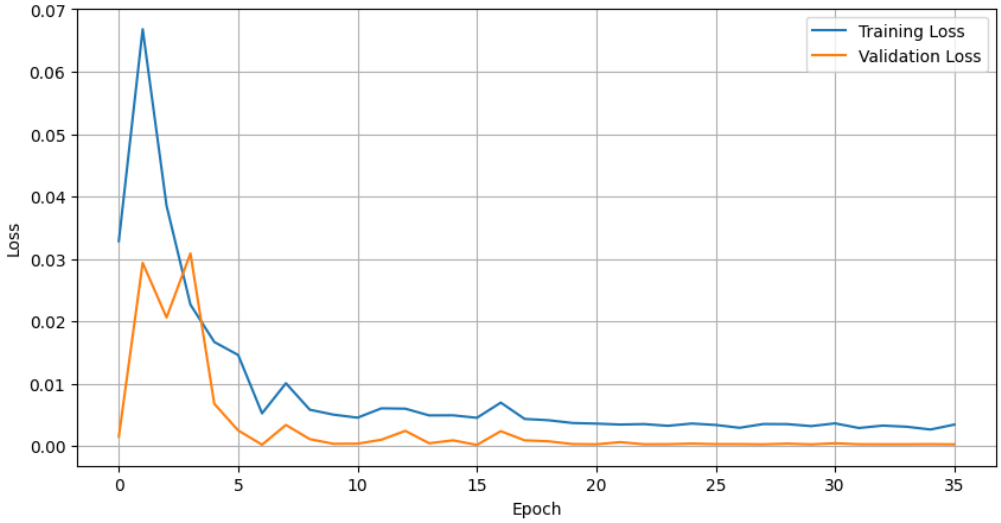


Figure 5 LSTM Training and Validation Loss

Feature Importance

Feature importance analysis was conducted using the Extra Trees model to quantify the contribution of each feature to the prediction task, as presented in figure 6. The results clearly indicate that price-based features dominate the model, with Close, Low, Open, and High exhibiting the highest importance scores, suggesting that raw price information plays a central role in determining future price movements. In addition, the moving average feature MA_7 shows a notable contribution, indicating that short-term trend information enhances predictive capability. In contrast, more complex technical indicators such as RSI, MACD, and Signal Line contribute minimally, reflecting their limited influence within the context of this dataset and feature set. This distribution of importance values highlights that the model relies primarily on fundamental price dynamics and simple trend indicators rather than derived momentum-based features.

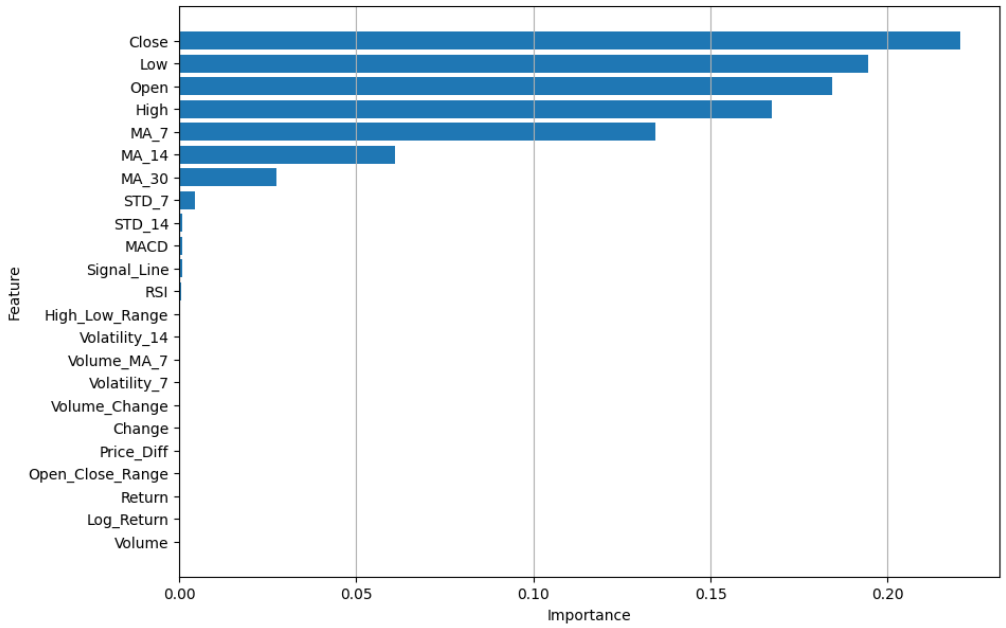


Figure 6 Feature Importance Using Extra Trees

Discussion

The results of this study indicate that traditional machine learning models, particularly Linear Regression and Ridge Regression, achieve superior predictive performance compared to the LSTM model when applied to the Solana price dataset [21], [22]. This outcome suggests that the underlying relationships between the input features and the target variable can be effectively captured using relatively simple linear approaches. A major contributing factor is the use of extensive feature engineering, in which technical indicators such as moving averages, returns, and volatility measures transform raw time-series data into a structured representation [23]. This transformation reduces the complexity of the learning task by incorporating relevant temporal and trend information directly into the features, allowing linear models to represent the data efficiently. The high coefficient of determination obtained by the Linear Regression model further supports this observation, indicating that most of the variability in the target variable is explained by the selected features.

In contrast, the LSTM model demonstrates significantly lower predictive accuracy, which can be attributed to several factors related to both data characteristics and model design [24]. The relatively limited dataset size may restrict the model's ability to learn complex temporal dependencies, as deep learning approaches generally benefit from sufficient training data to achieve effective generalization. In addition, the use of engineered features may reduce the advantage of sequence-based learning because much of the temporal information is already encoded in the input variables [25]. The prediction behavior of the LSTM model, which appears smoother and less responsive to sudden price changes, indicates a tendency to capture general trends rather than short-term fluctuations. This limitation is particularly relevant in cryptocurrency markets, where rapid and irregular price movements are common. Furthermore, the feature importance analysis reveals that basic price variables dominate the prediction process, while more complex indicators

contribute minimally. This finding suggests that simpler representations of price dynamics may be more informative for the forecasting task examined in this study [26].

Conclusion

This study developed and evaluated a predictive framework for forecasting Solana cryptocurrency prices using a Long Short-Term Memory model alongside several machine learning approaches, including Linear Regression, Ridge Regression, Random Forest, Extra Trees, and Gradient Boosting. The experimental results show that Linear Regression achieved the best performance across all evaluation metrics, indicating that the relationships between the input features and the target variable can be effectively modeled using simpler methods. The strong performance of linear models is closely related to the use of extensive feature engineering, where technical indicators and price-based variables transform the original time series into a more structured and informative representation. In contrast, the LSTM model demonstrated lower predictive accuracy, which can be attributed to the relatively limited dataset size and the reduced need for temporal sequence modeling when informative features are already available. Furthermore, the feature importance analysis confirms that fundamental price variables such as Close, Open, High, and Low are the most influential predictors, while more complex indicators such as RSI and MACD contribute minimally. These findings suggest that model effectiveness depends not only on model complexity but also on the nature of the data and the quality of feature representation, and they highlight the importance of selecting an appropriate modeling approach that aligns with the characteristics of the dataset.

Declarations

Author Contributions

Conceptualization: R.E., P.G.; Methodology: R.E., P.G.; Software: S.M., K.S.; Validation: P.G., K.S.; Formal Analysis: R.E.; Investigation: S.M., K.S.; Resources: P.G., K.S.; Data Curation: S.M.; Writing – Original Draft Preparation: R.E.; Writing – Review and Editing: P.G., K.S.; Visualization: S.M.; 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.

References

[1] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System," Aug. 21, 2008. Online. Available: https://ssrn.com/abstract=3440802.

[2] Y. Liu and A. Tsyvinski, "Risks and Returns of Cryptocurrency," *The Review of Financial Studies*, vol. 34, no. 6, pp. 2689–2727, Jun. 2021, doi: 10.1093/rfs/hhaa113.

[3] G. T. Wilson, "Book Review: Time Series Analysis: Forecasting and Control, 5th Edition, by G. E. P. Box, G. M. Jenkins, G. C. Reinsel and G. M. Ljung," *Journal of Time Series Analysis*, Mar. 2016, doi: 10.1111/jtsa.12194.

[4] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, Nov. 15, 1997, doi: 10.1162/neco.1997.9.8.1735.

[5] J. B. Heaton, N. G. Polson, and J. H. Witte, "Deep learning for finance: deep portfolios," *Applied Stochastic Models in Business and Industry*, vol. 33, no. 1, pp. 3–12, Jan./Feb. 2017, doi: 10.1002/asmb.2209.

[6] S. Lahmiri and S. Bekiros, "Cryptocurrency forecasting with deep learning chaotic neural networks," *Chaos, Solitons & Fractals*, vol. 118, no. January, pp. 35–40, Jan. 2019, doi: 10.1016/j.chaos.2018.11.014.

[7] L. Kristoufek, "What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis," *PLoS ONE*, vol. 10, no. 4, p. e0123923, Apr. 2015, doi: 10.1371/journal.pone.0123923.

[8] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.

[9] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *The Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, Oct. 2001, doi: 10.1214/aos/1013203451.

[10] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, Sep. 1995, doi: 10.1007/BF00994018.

[11] S. McNally, J. Roche, and S. Caton, "Predicting the Price of Bitcoin Using Machine Learning," in *2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP)*, Cambridge, UK, 2018, vol. 2018, no. June, pp. 339–343, doi: 10.1109/PDP2018.2018.00060.

[12] S. Ji, J. Kim, and H. Im, "A Comparative Study of Bitcoin Price Prediction Using Deep Learning," *Mathematics*, vol. 7, no. 10, p. 898, pp. 1-20, Sep. 2019, doi: 10.3390/math7100898.

[13] Z. Hu, Y. Zhao, and M. Khushi, "A Survey of Forex and Stock Price Prediction Using Deep Learning," *Applied System Innovation*, vol. 4, no. 1, p. 9, pp. 1-30, Feb. 2021, doi: 10.3390/asi4010009.

[14] K. Chen, Y. Zhou, and F. Dai, "A LSTM-based method for stock returns prediction: A case study of China stock market," in *Proceedings of the 2015 IEEE International Conference on Big Data (Big Data)*, vol. 2015, no. December, pp. 2823–2824,

2015, doi: 10.1109/BigData.2015.7364089.

[15] S. Siami-Namini, N. Tavakoli, and A. S. Namin, “The Performance of LSTM and BiLSTM in Forecasting Time Series,” in *2019 IEEE International Conference on Big Data (Big Data)*, Los Angeles, CA, USA, vol. 2020, no. February, pp. 3285–3292, 2019, doi: 10.1109/BigData47090.2019.9005997.

[16] T. Fischer and C. Krauss, “Deep learning with long short-term memory networks for financial market predictions,” *European Journal of Operational Research*, vol. 270, no. 2, pp. 654–669, Oct. 2018, doi: 10.1016/j.ejor.2017.11.054.

[17] L. Zhang, C. Aggarwal, and G.-J. Qi, “Stock Price Prediction via Discovering Multi-Frequency Trading Patterns,” in *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’17)*, vol. 2017, no. August, pp. 2141–2149, 2017, doi: 10.1145/3097983.3098117.

[18] J. Nasir, H. Iftikhar, M. Aamir, H. Iftikhar, P. C. Rodrigues, and M. Z. Rehman, “A Hybrid LMD–ARIMA–Machine Learning Framework for Enhanced Forecasting of Financial Time Series: Evidence from the NASDAQ Composite Index,” *Mathematics*, vol. 13, no. 15, p. 2389, pp. 1-18, Jul. 2025, doi: 10.3390/math13152389.

[19] J. W. Wilder, *New Concepts in Technical Trading Systems*. Greensboro, NC, USA: Trend Research, 1978.

[20] S. B. Achelis, *Technical Analysis from A to Z*, 2nd ed. New York, NY, USA: McGraw-Hill Professional, 2000.

[21] N. Uras, L. Marchesi, M. Marchesi, and R. Tonelli, “Forecasting Bitcoin closing price series using linear regression and neural networks models,” *PeerJ Comput. Sci.*, vol. 6, no. 1, pp. 1–15, 2020, doi: 10.7717/peerj-cs.279.

[22] R. Hasanli and M. Dursun, “Integrating high-dimensional technical indicators into machine learning models for predicting cryptocurrency price movements and trading performance: Evidence from Bitcoin, Ethereum, and Ripple,” *FinTech*, vol. 4, no. 4, pp. 1–20, Dec. 2025, doi: 10.3390/fintech4040077.

[23] R. de Aquino Silva, A. S. R. Pinto, G. D. de Araújo, and L. Ricci, “A novel cryptocurrency trend prediction framework powered by innovative feature engineering,” *IEEE Access*, vol. 14, no. 1, pp. 3722–3743, 2026, doi: 10.1109/ACCESS.2025.3640400.

[24] N. Verma, “Cryptocurrency price forecasting using LSTM: A review,” *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 2025, no. 1, pp. 1–10, 2025, doi: 10.22214/ijraset.2025.72248.

[25] M. Rafi, Q. Mirza, M. Sohail, M. L. Aliasghar, A. Aziz, and S. Hameed, “Enhancing cryptocurrency price forecasting accuracy: A feature selection and weighting approach with bi-directional LSTM and trend-preserving model bias correction,” *IEEE Access*, vol. 11, no. 1, pp. 65700–65710, 2023, doi: 10.1109/ACCESS.2023.3287888.

[26] S. Singh, A. Pise, and B.-W. Yoon, “Prediction of Bitcoin stock price using feature subset optimization,” *Heliyon*, vol. 10, no. 1, pp. 1–15, 2024, doi: 10.1016/j.heliyon.2024.e28415.