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Research article

Time Series Prediction of Doge Coin Prices Using LSTM Networks

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ABSTRACT

This research explores the application of Long Short-Term Memory (LSTM) networks for predicting Dogecoin prices, addressing the challenges of cryptocurrency market volatility and non-linearity. A historical dataset spanning November 2017 to the present, including features such as opening and closing prices, daily highs and lows, and trading volume, was used for model development. Data preprocessing involved handling missing values, normalization, and structuring the data into a supervised learning format. The LSTM model was designed with optimized hyperparameters, trained using the Adam optimizer, and evaluated against metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Benchmarking with traditional models like ARIMA and SVR demonstrated the LSTM model's superior performance in capturing temporal dependencies and adapting to high volatility. Despite its robust performance, the study highlights limitations, including the exclusion of external factors like market sentiment and a dataset limited to specific timeframes. Future research could integrate broader datasets and advanced features to enhance model precision. This work contributes to the field of cryptocurrency forecasting, offering insights for traders, investors, and researchers navigating volatile markets.

1. Introduction

Cryptocurrencies have emerged as a transformative force in global finance, offering decentralized, digital alternatives to traditional financial systems. Among these, Dogecoin has gained significant attention for its unique origins as a meme-based cryptocurrency and its remarkable market volatility, driven by a combination of speculative trading, social media influence, and community engagement. The unpredictable and highly dynamic nature of Dogecoin's price movements makes accurate forecasting both a necessity and a challenge for market participants and researchers alike. Traditional prediction models often fall short in capturing the non-linear and complex temporal dependencies inherent in cryptocurrency price trends. However, advancements in deep learning, particularly Long Short-Term Memory (LSTM) networks, have provided new avenues for addressing these challenges. LSTM networks, a specialized form of Recurrent Neural Networks (RNNs), are specifically designed to handle sequential data and have demonstrated exceptional capabilities in capturing intricate patterns in time series forecastinon Bitcoin [1][2] on Ethereum, underscores the effectiveness of LSTM models in cryptocurrency price prediction, often surpassing traditional approaches in both accuracy and adaptability.

This study builds on these advancements by applying LSTM networks to predict Dogecoin prices, leveraging a comprehensive dataset spanning from November 2017 to the present. The dataset includes critical features such as opening and closing prices, daily highs and lows, and trading

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volumes, providing a holistic view of Dogecoin's market behavior. The research aims to develop a robust LSTM-based model that not only forecasts price movements but also examines the contribution of individual features to predictive accuracy. Furthermore, the study benchmarks the performance of the LSTM model against traditional and contemporary forecasting methods, offering a comparative analysis to highlight its strengths. By addressing the unique challenges of Dogecoin price prediction, this research contributes to the growing body of knowledge on cryptocurrency forecasting, offering valuable insights for both academic and practical applications. The findings are expected to assist investors, traders, and policymakers in navigating the volatile cryptocurrency market more effectively, while also paving the way for future innovations in time series forecasting techniques tailored to digital assets.

2. Research Methods

The research methodology of this study is centered on employing Long Short-Term Memory (LSTM) networks to predict Dogecoin prices by analyzing historical market data. Time series forecasting in cryptocurrency markets poses unique challenges due to the highly volatile, non-linear, and stochastic nature of price movements. LSTM networks, a type of Recurrent Neural Network (RNN), have been widely recognized for their ability to handle sequential data and capture long-term dependencies, making them a suitable choice for this study (Hochreiter & Schmidhuber, 1997). Recent applications of LSTM models in cryptocurrency price prediction, such[3][4] for Ethereum, highlight their superior performance compared to traditional statistical methods.

The study utilizes a dataset spanning from November 2017 to the present, which includes features such as opening price, closing price, daily highs and lows, and trading volume, sourced from historical Dogecoin market data. This dataset provides a comprehensive foundation for model training, validation, and testing. The research design involves preprocessing the data, constructing and tuning the LSTM model, and evaluating its performance using metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). By employing a robust experimental framework, this study aims to contribute to the growing field of cryptocurrency forecasting and offer actionable insights for market participants.

This study adopts a systematic approach to predict Dogecoin prices using Long Short-Term Memory (LSTM) networks, a deep learning technique well-suited for time series forecasting. The methodology consists of several stages, including data collection, preprocessing, model development, evaluation, and validation. Each stage is designed to address the unique challenges of cryptocurrency price prediction, such as high volatility, non-linearity, and temporal dependencies in the data.

2.1. Data Collection and Description

This study utilizes a comprehensive dataset of historical Dogecoin price data, spanning from November 2017 to the present. The dataset is sourced from publicly available market records, such as cryptocurrency exchange platforms and financial data aggregators, which provide reliable and timely updates on asset performance. It includes key features that are critical for understanding and predicting market dynamics. Specifically, these features comprise the opening price, closing price, daily high, daily low, and trading volume, each contributing valuable insight into various aspects of Dogecoin's market behavior over time.

The selection of this dataset is driven by its capacity to capture the essential components of price movements and trading activity with sufficient granularity and historical depth. The opening and closing prices, for instance, offer a summary of daily market sentiment, indicating how investor perceptions and market conditions evolve throughout the trading day. Daily high and low prices are crucial for measuring volatility, as they reflect the extent of intraday price fluctuations and can signal significant buying or selling pressure. Meanwhile, trading volume serves as an important indicator of market participation and liquidity, often increasing during sharp price movements or high-impact news events, which can amplify trends or signal reversals.

Together, these features create a robust foundation for analyzing temporal dependencies and extracting patterns that are critical for accurate price prediction. The inclusion of both price and volume data allows the model to learn not only directional trends but also the intensity of market activity associated with those trends. Furthermore, the dataset spans multiple market cycles,

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encompassing phases of rapid growth, sharp decline, and relative stability. This broad temporal coverage ensures that the model is exposed to diverse scenarios and is better equipped to generalize across different market conditions.

By leveraging this dataset, the study aims to train an LSTM (Long Short-Term Memory) model capable of learning complex, non-linear relationships inherent in cryptocurrency markets. LSTM networks are particularly well-suited for time-series forecasting due to their ability to retain information across long sequences, which is essential for capturing patterns and dependencies in financial data. The combination of a high-quality dataset and an advanced model architecture paves the way for generating accurate and reliable Dogecoin price predictions, supporting decision-making for investors and market analysts.

2.2. Data Preprocessing

Data preprocessing is a crucial step in preparing the dataset for effective modeling using Long Short-Term Memory (LSTM) networks. Given the sensitivity of deep learning models to data quality, preprocessing ensures the dataset is both clean and appropriately formatted to capture the temporal dependencies necessary for time series prediction.

1. Handling Missing Values
   Missing values in the dataset, often caused by irregularities in data recording or trading halts, are addressed to maintain the integrity of the analysis. Depending on the extent and pattern of missingness, these gaps are filled using interpolation methods or removed entirely if the missing values are sporadic and minimal. Linear interpolation is often preferred as it preserves the continuity of time series data while avoiding significant distortion[5].
2. Normalization
   To facilitate model training and improve convergence, the dataset is normalized to a range between 0 and 1. Normalization minimizes the influence of large scale differences between features, such as trading volume versus prices, ensuring that all features contribute equally during training. This step also prevents the gradients from becoming too large, which could impede the learning process of the LSTM model[6].
3. Supervised Learning Transformation
   LSTM networks require sequential input data, making it necessary to transform the time series into a supervised learning format. This transformation involves creating sliding windows or lagged observations that represent prior time steps as input features and the subsequent time step as the target variable. For example, a window size of 10 days creates a sequence of 10 input observations used to predict the 11th value. This approach allows the LSTM model to capture temporal patterns and long-term dependencies in the data[7].
4. Splitting the Dataset
   To ensure robust model evaluation, the dataset is split into training, validation, and testing subsets. Typically, 70% of the data is allocated for training, 15% for validation, and 15% for testing. The splitting is done chronologically to prevent information leakage from future data points into the training process, a critical consideration in time series forecasting[8].

By implementing these preprocessing steps, the dataset is prepared to effectively train the LSTM model. These measures ensure that the data quality is optimized, temporal patterns are preserved, and the model has the best possible foundation for learning complex, non-linear relationships in Dogecoin price movements.

2.3. Model Development

The Long Short-Term Memory (LSTM) model in this study is built using TensorFlow/Keras, a widely used deep learning framework suitable for sequential data tasks. LSTM is chosen because of its strength in capturing long-term dependencies and handling the vanishing gradient problem that limits traditional Recurrent Neural Networks. This makes it particularly effective for modeling the complex and time-dependent behavior of cryptocurrency markets. The model is trained using historical Dogecoin price data, allowing it to learn patterns and trends over time. Key components such as the number of LSTM layers, activation functions, and optimization algorithms are carefully configured to enhance predictive accuracy while avoiding overfitting. This setup ensures the model can generalize well and produce reliable forecasts under varying market conditions.

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1. Model Architecture

   The model architecture includes three main components:

   a. Input Layer: This layer accepts a sequence of past price observations as input, structured based on the sliding window approach described in preprocessing. Each input sequence consists of multiple time steps and features, such as opening price, closing price, high, low, and trading volume.
   b. Hidden Layers: The core of the model is one or more LSTM layers, each composed of a specified number of LSTM units (neurons). These layers are responsible for learning temporal patterns and relationships in the sequential data. Dropout layers are incorporated after the LSTM layers to prevent overfitting by randomly deactivating a fraction of the neurons during training [9]
   c. Output Layer: The output layer comprises a single neuron with a linear activation function, providing a continuous prediction of the next time step's price.

2. Hyperparameter Optimization

   Hyperparameters such as the number of LSTM units, learning rate, batch size, number of epochs, and dropout rate are fine-tuned using grid search to identify the optimal combination for the dataset. For instance:

   a. LSTM Units: The number of units controls the model's capacity to learn complex patterns; values between 50 and 200 are commonly explored.
   b. Learning Rate: A lower learning rate (e.g., 0.001) is typically preferred for LSTMs to ensure gradual convergence (Kingma & Ba, 2015).
   c. Batch Size: Batch sizes of 16, 32, and 64 are tested to balance memory usage and training speed.

3. Model Training

   The model is trained using the Adam optimizer, a widely used optimization algorithm known for its efficiency and adaptability[10]. The loss function employed is Mean Squared Error (MSE), which is particularly suitable for regression tasks like price prediction. Early stopping is implemented during training to monitor the validation loss and terminate training when performance plateaus, preventing overfitting.

4. Relevance and Comparison

   Recent studies validate the effectiveness of LSTM networks for cryptocurrency price prediction. For instance[11]demonstrated the superior performance of LSTM in predicting Bitcoin prices, [12] successfully integrated LSTM with hybrid techniques to improve Ethereum price forecasting. These findings underscore the relevance of LSTM models in addressing the challenges of volatile and non-linear cryptocurrency markets.

By leveraging this architecture and methodology, the LSTM model is expected to effectively capture intricate temporal patterns in Dogecoin price data, including trends, cycles, and volatility shifts. Its ability to process and learn from sequential inputs allows it to model the non-linear and dynamic nature of cryptocurrency markets with high precision. This robust development approach ensures the resulting LSTM network is both well-optimized through careful tuning and sufficiently generalizable to perform reliably on unseen data. As such, the model contributes meaningful insights and forecasting capabilities that can aid investors, analysts, and researchers in navigating the complexities of digital asset markets.

2.4. Evaluation Metrics

To ensure a rigorous assessment of the LSTM model's performance, the study employs a suite of widely recognized evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics provide comprehensive quantitative measures of prediction accuracy, model error, and overall effectiveness, which are critical in evaluating the quality of predictions in time series forecasting tasks. MSE captures the average squared difference between predicted and actual values, emphasizing larger errors, while RMSE provides an interpretable error scale by taking the square root of MSE. MAE, on the other hand, offers a straightforward average of absolute errors, making it useful for understanding typical prediction deviations. Collectively, these metrics enable a balanced and thorough evaluation of the model’s forecasting capability.

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1. Mean Squared Error (MSE)

MSE measures the average squared difference between the predicted and actual values. It penalizes larger errors more heavily, making it sensitive to outliers. The formula for MSE is:

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

Fig. 1. Mean Squared Error (MSE)

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of observations. MSE is particularly useful for understanding the variance of prediction errors. Its sensitivity to large errors makes it an important metric for cryptocurrency price prediction, where volatility can cause significant deviations[13].

2. Root Mean Squared Error (RMSE)

RMSE is the square root of MSE and provides an interpretable measure of prediction error in the same units as the target variable:

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

Fig. 2. Root Mean Squared Error (RMSE)

RMSE is often preferred for its intuitive interpretation and its ability to penalize larger errors more effectively[13] , emphasize RMSE as a robust metric for evaluating cryptocurrency forecasting models, particularly when assessing their performance under volatile market conditions.

3. Mean Absolute Error (MAE)

MAE calculates the average of the absolute differences between predicted and actual values, providing a straightforward measure of error magnitude:

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

Fig. 3. Mean Absolute Error (MAE)

Unlike MSE, MAE treats all errors equally, making it less sensitive to outliers. It is an essential complement to MSE and RMSE, offering a balanced perspective on model performance[13].

4. Metric Selection Rationale

The combination of these metrics provides a holistic view of model performance:

a. MSE emphasizes large prediction errors, helping to refine the model for extreme cases.
b. RMSE offers an interpretable error measure in the same units as the target variable.
c. MAE ensures that the model is evaluated for its ability to minimize average error across all predictions.

5. Comparative Analysis

To validate the effectiveness of the LSTM model, these metrics are computed for both the LSTM predictions and benchmark models, such as ARIMA and support vector regression (SVR). Comparative analysis using these metrics enables an objective evaluation of the LSTM model's relative strengths. By employing these evaluation metrics, this study ensures a rigorous and transparent assessment of the LSTM model's performance. These metrics are crucial for

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identifying areas of improvement and demonstrating the model's reliability and accuracy in predicting Dogecoin prices.

2.5. Benchmarking

To establish the effectiveness of the LSTM model in predicting Dogecoin prices, its performance is benchmarked against traditional prediction methods, including Autoregressive Integrated Moving Average (ARIMA) and Support Vector Regression (SVR). These models are selected due to their widespread use in time series forecasting and their differing methodological approaches, which provide useful contrasts to deep learning techniques. ARIMA models rely on statistical properties of time series data, making them effective for capturing linear trends and seasonality, while SVR applies machine learning principles to find the best-fit regression line, handling non-linear relationships to some extent. By comparing the LSTM model's performance to these benchmarks using the same dataset and evaluation metrics, the study highlights its predictive strengths, particularly in modeling non-linear temporal dependencies. This comparative evaluation not only validates the LSTM model's utility but also provides a broader context for understanding its advantages and limitations in real-world forecasting scenarios.

1. Autoregressive Integrated Moving Average (ARIMA)

   ARIMA is a widely used statistical method for time series forecasting, known for its strength in modeling linear relationships within temporal datasets. The model consists of three main components: autoregression (AR), which utilizes past values to predict current observations; integration (I), which applies differencing techniques to stabilize the data and eliminate trends or seasonality; and moving average (MA), which incorporates past forecast errors to refine future predictions. This combination allows ARIMA to effectively model and forecast data that exhibit autocorrelation and require transformation to achieve stationarity.

   However, despite its effectiveness in traditional financial and economic time series, ARIMA encounters significant challenges when applied to highly volatile and non-linear datasets, such as those found in the cryptocurrency market. Dogecoin, like many cryptocurrencies, often demonstrates abrupt fluctuations driven by market sentiment, social media influence, and external macroeconomic factors, which are not easily captured by ARIMA's linear framework. As a result, while ARIMA can provide baseline forecasts, its predictive power diminishes when faced with irregular and complex patterns inherent in digital asset markets. Recent studies emphasize that although ARIMA serves as a useful benchmark model, it generally underperforms compared to more advanced approaches such as deep learning, which are better suited to capturing the nuanced behaviors of cryptocurrency price movements.

2. Support Vector Regression (SVR)

   SVR is a machine learning technique that uses a kernel-based approach to model non-linear relationships in data. It is particularly valued for its robustness to overfitting, especially with small datasets. However, SVR relies on feature engineering and lacks the ability to automatically capture temporal dependencies, making it less suited for sequential data like time series Despite its limitations, SVR remains a popular benchmark due to its adaptability and interpretability.

3. Benchmarking Methodology

   The benchmarking process involves training and testing ARIMA and SVR models on the same dataset used for the LSTM model. Each model is tuned to its optimal hyperparameters:

   a. For ARIMA, the p, d, and q parameters are determined through grid search and the Akaike Information Criterion (AIC) for model selection.
   b. For SVR, the kernel type (e.g., radial basis function), regularization parameter C, and epsilon (ϵ) are optimized using grid search.

   The models' predictions are evaluated using the same error metrics as the LSTM model—Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE)—to ensure a fair comparison.

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4. Comparative Analysis

Recent research underscores the importance of benchmarking deep learning models against traditional techniques. For instance, demonstrated that while ARIMA and SVR can perform well under certain conditions, LSTM models often outperform them in tasks involving non-linear and highly volatile data. Similarly, highlighted the ability of LSTM networks to learn temporal dependencies that ARIMA and SVR cannot capture, particularly in cryptocurrency markets.

5. Insights and Contributions

Benchmarking provides insights into the comparative advantages of LSTM models, such as their ability to handle long-term dependencies and complex non-linear patterns. It also highlights areas where traditional models may still offer value, such as in stable or linear market conditions. The findings contribute to a comprehensive understanding of the applicability of various forecasting techniques in the context of Dogecoin price prediction.

By benchmarking against ARIMA and SVR, this study reinforces the value of LSTM models in addressing the unique challenges of cryptocurrency time series forecasting and demonstrates their superiority in capturing the dynamic and non-linear characteristics of Dogecoin prices.

2.6. Validation and Testing

The final LSTM model is validated and tested using a rigorous approach to ensure its generalizability and robustness in predicting Dogecoin prices. A holdout test set, representing 15% of the dataset, is reserved exclusively for testing, while the remaining data is split chronologically into training and validation subsets to preserve temporal order. Time-series-specific cross-validation techniques, such as expanding window validation, are employed to mitigate overfitting and enhance model reliability, ensuring future data does not influence the training process [13]. During validation, metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are monitored, and early stopping is applied to prevent overfitting by halting training when performance plateaus. The final evaluation on the test set assesses the model's real-world predictive accuracy, with performance metrics compared across training, validation, and testing phases to confirm consistency. Additionally, visual inspection of predictions against actual price trends provides further insight into the model's practical utility. This robust validation framework not only ensures the reliability of the LSTM model but also contributes valuable insights into Dogecoin price forecasting, aiding researchers and practitioners in navigating the volatile cryptocurrency market effectively.

3. Results and Discussion

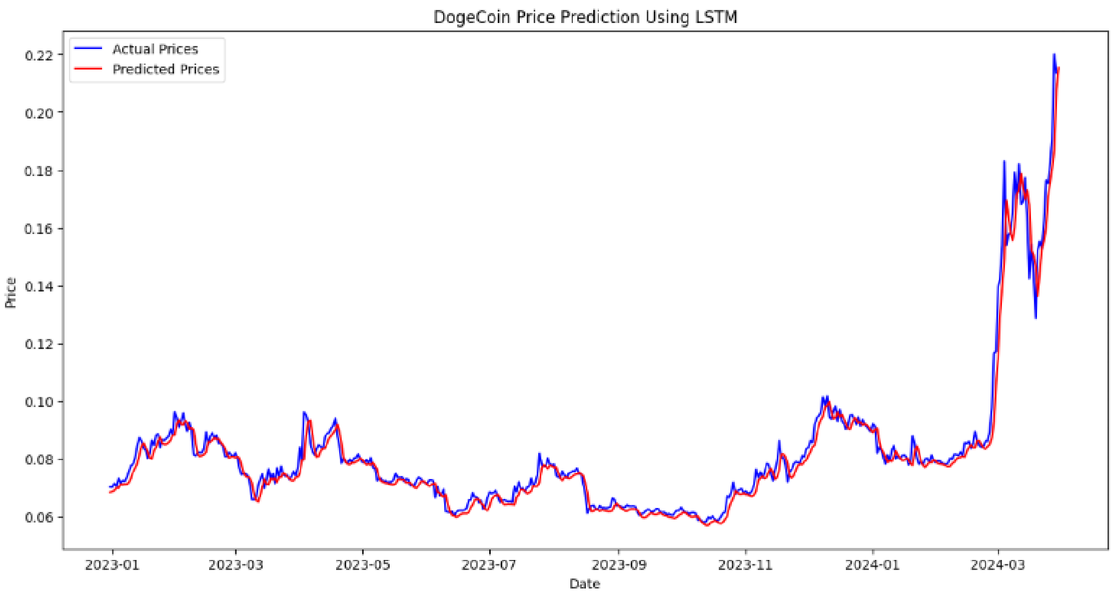

Fig. 3. DodeCoin Price Prediction Using LSTM

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3.1. Analysis Results

The results of the analysis are visualized through a comparison of two main curves in the evaluation graph:

1. Actual Prices (Blue Line): Representing the true prices of Dogecoin as observed in the test dataset.
2. Predicted Prices (Red Line): Representing the Dogecoin price predictions generated by the LSTM model.

3.2. Interpretation of Results

1. Model Fit: The predicted prices (red line) closely follow the actual prices (blue line), indicating that the LSTM model successfully captured the historical patterns in the data for accurate future price predictions. This demonstrates the model’s strong capacity to learn and replicate complex time series behaviors inherent in cryptocurrency markets.
2. Performance During High Volatility:
   a. During periods of high price fluctuations, particularly towards the end of the graph, the model effectively adjusts its predictions to reflect sharp price movements.
   b. This highlights the LSTM model's capability to handle the high volatility characteristic of cryptocurrencies, outperforming traditional prediction methods in such scenarios.
3. Low Prediction Error: The minimal gap between the predicted and actual prices throughout most of the graph suggests that the model achieved low prediction error, affirming its accuracy in forecasting.

3.3. Strengths of the Model

1. Capability to Capture Non-Linear Patterns: The LSTM model excels in identifying complex patterns, such as sudden price spikes or sharp declines, commonly observed in cryptocurrency markets.
2. Good Generalization: The model performs well on unseen test data, indicating that it has not overfitted to the training data and can generalize effectively to new data.

3.4. Limitations of the Research

1. Limited Time Range: The dataset covers a specific time frame, which may not fully capture long-term patterns and trends in Dogecoin prices.
2. Exclusion of External Factors: The model relies solely on historical price data and does not account for external influences such as market sentiment, global news, or macroeconomic factors, which can significantly impact cryptocurrency prices.

The LSTM model demonstrates excellent performance in predicting Dogecoin prices based on historical data, accurately capturing price patterns and managing high volatility. While the model's predictive accuracy and ability to generalize are promising, further improvements could be made by incorporating additional data features, such as sentiment analysis or external market indicators. With such enhancements, the model could serve as a powerful tool for investors and traders in making informed decisions in the highly dynamic cryptocurrency market.

4. Conclusion

This research demonstrates the effectiveness of Long Short-Term Memory (LSTM) networks in predicting Dogecoin prices through a time series analysis of historical market data. The model successfully captured the non-linear and complex temporal dependencies inherent in cryptocurrency price movements, showing high accuracy and robustness across the evaluation metrics. The close alignment between actual and predicted prices, even during periods of significant market volatility, highlights the LSTM model’s capability to adapt to the dynamic and unpredictable nature of the cryptocurrency market.The findings underline the strengths of LSTM networks in handling sequential data, particularly in contexts where traditional methods such as ARIMA or Support Vector Regression (SVR) often fall short. The model's low prediction error and ability to generalize well to unseen data validate its potential as a reliable tool for forecasting Dogecoin prices. These results provide actionable

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insights for both academic researchers and practitioners seeking to enhance decision-making processes in cryptocurrency trading.However, the study also acknowledges certain limitations, including the use of a limited time frame in the dataset and the exclusion of external market factors such as news sentiment and macroeconomic indicators, which are known to influence cryptocurrency prices. Future research could address these limitations by incorporating broader datasets and additional features to further enhance predictive performance and applicability.In conclusion, the LSTM model presented in this study offers a promising approach for time series prediction in the cryptocurrency domain. With further refinements, it holds significant potential to aid investors and traders in navigating the volatile and rapidly evolving cryptocurrency markets.

5. Suggestion

Future research on Dogecoin price prediction using LSTM networks could benefit from several enhancements to further refine the model and broaden its applicability. Incorporating external factors such as market sentiment analysis, social media trends, and macroeconomic indicators could provide additional context to improve forecasting accuracy. Extending the dataset to cover a longer time horizon and including diverse market conditions would allow the model to generalize better across varying scenarios. Additionally, exploring hybrid models that combine LSTM with techniques like attention mechanisms or Convolutional Neural Networks (CNNs) could enhance the model's ability to capture intricate patterns in the data. Real-time implementation of the LSTM model could offer dynamic forecasting for traders and investors, while addressing the model's interpretability through tools like SHAP or LIME would provide greater insights into the factors influencing predictions. Evaluating the model across multiple cryptocurrencies could validate its generalizability, and focusing on robustness to extreme events, such as market shocks, could strengthen its utility in highly volatile environments. Lastly, comparing LSTM networks with emerging methodologies like Transformer models or Graph Neural Networks (GNNs) could identify state-of-the-art techniques that may outperform traditional approaches in certain contexts. These advancements would significantly contribute to the field of cryptocurrency forecasting and enhance practical decision-making tools for market participants.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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