
DOGECOIN PRICE PREDICTION USING HISTORICAL DATA AND SOCIAL MEDIA TRENDS

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ABSTRACT

INTRODUCTION: Cryptocurrency is digital and digital money based on blockchain technology, which ensures transaction security. In recent years, the number of cryptocurrencies has increased dramatically. Notably, Bitcoin and Ethereum have emerged as fascinating research topics in finance. By 2021, more than 4,000 cryptocurrencies have been listed. While various research has attempted to anticipate cryptocurrency prices using machine learning, most have focused primarily on Bitcoin.

OBJECTIVES: In this research, we provide a deep learning model for predicting the price of dogecoin cryptocurrency. This model is based on historical market price data for Dogecoin cryptocurrency.

METHODS: The Dogecoin market data was sourced from Investing.com at a daily level. Experimental results show that the suggested model provides a promising prediction for the future price of Dogecoin, a cryptocurrency that has lately gained popularity in the crypto market.

RESULTS: The dataset OCVP (Open, Close, High, Volume) variables resulted in a minimum RMSE of 0.003 in predicting the Dogecoin price. Experimental results suggest that the proposed strategy is effective..

Keywords Dogecoin, Doge, Cryptocurrency, Deep Learning

1 Introduction

Cryptocurrency represents an important change in the digital banking sector, utilizing blockchain technology to assure secure, transparent, and immutable transactions. Since Bitcoin's debut in 2009, the cryptocurrency industry has grown tremendously, with over 4,000 cryptocurrencies listed by 2021. This quick expansion has caught the interest of researchers, investors, and legislators alike, in addition to receiving major media coverage. Among these digital currencies, Bitcoin and Ethereum have emerged as prominent research topics, owing to their market volatility, potential for big rewards, and unique technological foundations.

While much of the existing literature has focused on projecting price changes for Bitcoin and Ethereum, there has been relatively little research into alternative cryptocurrencies, or "altcoins." Dogecoin is one example of a cryptocurrency that has sparked widespread interest. Dogecoin was founded in 2013 as a spoof of the cryptocurrency craze, but it has since grown into a genuine participant in the digital currency field, with a thriving community and a distinct cultural importance. Its price movements are significantly influenced by a number of factors, including social media trends, celebrity endorsements, and broader market attitudes, making it an appealing option for predictive analysis.

This study seeks to fill a gap in the existing literature by creating a robust deep learning model designed exclusively for predicting Dogecoin prices. Unlike traditional financial instruments, the cryptocurrency market is known for its extreme volatility and vulnerability to quick price movements, emphasizing the need for sophisticated prediction tools. Using historical market price data from Investing.com, this study aims to investigate the effectiveness of deep learning approaches in capturing the complex patterns and trends inherent in Dogecoin price fluctuations. The technique used in this study is a thorough examination of Dogecoin market data, with a focus on key characteristics such as opening price, closing price, trading volume, and market sentiment (polarity). This technique aims to assess the prediction capabilities of deep learning models as well as their potential applications in the cryptocurrency industry. The results of this study show that the suggested model has good predictive performance, with a minimum Root Mean Square Error (RMSE) of 0.003.

This paper not only improves to the intellectual debate around Dogecoin by expanding our understanding of price dynamics in the cryptocurrency market, but it also gives practical insights for traders and investors navigating this rapidly shifting landscape. The findings show that advanced machine learning algorithms can improve price forecast accuracy, allowing for more informed decision-making in an increasingly dynamic market situation.

2 Main Text and Analysis

2.1 Data Collection and Preprocessing

The dataset includes historical Dogecoin statistics at the daily level, collected from Investing.com. Each day's key elements include the starting and closing prices, high and low prices, and trading volume. Preprocessing activities were crucial in ensuring data quality and model readiness. This included filling in any missing values, standardizing feature values, and normalizing the dataset to improve consistency and prepare it for input into the LSTM model. Normalization guarantees that all features are scaled identically, which is especially critical for models that use gradient descent.

The final feature vector had five key indications for each day: the opening price, closing price, daily high, daily low, and trading volume. This minimal feature set provides the required information for forecasting future price changes without relying on external sentiment data.

2.2 Model Selection and LSTM Architecture

LSTM networks, a subset of Recurrent Neural Networks (RNNs), are good for time-series forecasting because of their memory cells and gating mechanisms, which help manage and preserve relevant input over time. Unlike typical RNNs, LSTMs can capture longer dependencies by employing input, output, and forget gates to control the flow of information and avoid the vanishing gradient problem. This feature is especially useful for bitcoin prediction, as patterns are determined by both recent prices and longer-term trends.

Hyperparameter tuning was used to establish the model's optimal setup. Among the different optimizers examined, including Adadelta, Adagrad, SGD, and Adam, the Adam optimizer had the lowest RMSE and so was chosen. Additional hyperparameters, such as learning rate, epoch count, and batch size, were adjusted to increase performance. The chosen setup aimed to balance computing efficiency and predicted accuracy by using a learning

rate of 0.01, 50 epochs, and 32 batches.

3 Related Work

Research on bitcoin price prediction has progressed, with several machine learning models used to capture market intricacies. Liao (2023) emphasises the importance of historical data in projecting Bitcoin, Dogecoin, and Ethereum prices, emphasising model selection for reliable predictions [1]. DeVries (2016) and Wisetsri et al. (2022) highlight the speculative nature of cryptocurrencies and the significance of predictive modelling in investment planning [2] [3]. Medzihorský (2022) examines Dogecoin's price prediction, highlighting the issues caused by severe volatility [4].

Some research use social sentiment to increase prediction accuracy, as demonstrated by Bhatt et al. (2023) and Di Tollo et al. (2023), who combine social media data and machine learning models [5] [6]. Agarwal et al. (2021) discovered that sentiment is important for Dogecoin forecasts [7]. Tandon et al. (2021) and Nair et al. (2023), on the other hand, emphasise the efficacy of classic time-series models based solely on historical data [9, 11]. Studies by Reddy and Sriramya (2020) and Jaquart et al. (2021) confirm LSTM's strengths in cryptocurrency forecasting because to its temporal data preservation [15] [16].

This study builds on historical market data alone, using LSTM to provide a foundational model for Dogecoin prediction, offering insights for investors who prefer sentiment-free analysis.

Author	Model Used	Cryptocurrency	Dataset	Error	Remarks
Liao (2023)	Long Short-Term Memory (LSTM)	Bitcoin, Dogecoin, Ethereum	BCP Business & Management EMFRM	N/A	Uses historical price data to predict trends in multiple cryptocurrencies.
Medzihorský (2022)	Long Short-Term Memory (LSTM)	Dogecoin	Journal of Economics and Social Research	N/A	Focuses on Dogecoin price determinants and the impact of high volatility on predictions.
Bhatt et al. (2023)	LSTM with Social Media Sentiment	Bitcoin, Dogecoin	CMLA, GRAPH-HOC, CIoT, DMSE, ArIT, WiMoNe, CSEIT	N/A	Incorporates social sentiment with historical data; improves accuracy during high market activity.
Di Tollo et al. (2023)	Stochastic ANN with Sentiment Analysis	Bitcoin, Altcoins	Mathematics Journal	N/A	Leverages sentiment data and NLP to capture trends in cryptocurrency and stock market prices.
Agarwal et al. (2021)	LSTM with Social Media Trends	Dogecoin	EAI Endorsed Transactions	N/A	Uses social media trends as additional input for Dogecoin price predictions, enhancing model performance.

Nair et al. (2023)	Deep Learning (LSTM)	Bitcoin, Ethereum	Int. Journal of Advanced Computer Science and Applications	0.084 RMSE	Shows LSTM's effectiveness using time-series data, focusing on daily cryptocurrency price forecasting.
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4 Proposed Approach

This research aims to predict Dogecoin prices using Long Short-Term Memory (LSTM) neural networks based solely on historical market data. The proposed approach follows a structured methodology that includes data collection, preprocessing, feature selection, model design, hyperparameter tuning, and evaluation.

The model may be updated to anticipate Dogecoin values solely using past market data, excluding sentiment analysis. An alternative strategy that only uses conventional market indicators is as follows:

The suggested approach uses only historical market data to forecast Dogecoin cryptocurrency prices. The structure of this method is shown in Figure 1. The model operates as follows: first, we collect historical market data for Dogecoin at daily granularity over a given period. Important information is gathered every day, including the opening price, closing price, daily high and low prices, and trading volume.

We preprocess the data after it has been collected to handle any missing values, guarantee consistency, and normalize the characteristics. A feature vector that contains the crucial information required to predict future Dogecoin prices is then created using this processed data. Long short-term memory (LSTM) is a deep learning model well-known for its ability to effectively capture temporal dependencies in time-series data and receive the feature vector as input.

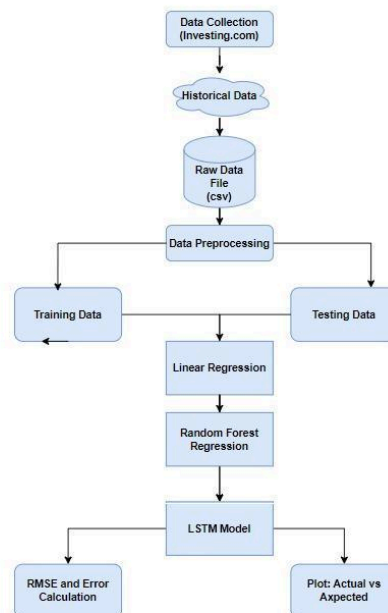


Fig 1, Overview of the proposed approach for predicting the dogecoin market price

4.1 Feature Selection

This study uses a limited but essential set of features that capture the primary price dynamics of Dogecoin. These

include:

Open Price: The initial trading price of Dogecoin on the observation day, representing the first recorded transaction of the day.

Close Price: The final trading price of Dogecoin at the end of the observation day, representing the last transaction before market closing.

Low Price: The lowest recorded trading price of Dogecoin throughout the day.

High Price: The highest recorded trading price of Dogecoin during the day.

Volume: The total quantity of Dogecoin traded over the course of the observation day.

Close	Closing price in the time period
High	Highest price in the time period
Low	Lowest price in the time period
Open	Opening price in the time period
Vol	Trading volume for the time period

Table 1. Feature set for deep learning model

4.2 Deep Learning model

Long Short-Term Memory (LSTM) networks have acquired popularity in the field of time series forecasting, particularly for predicting cryptocurrency prices like Dogecoin. LSTMs are a form of sophisticated recurrent neural network (RNN) that was created to solve the vanishing gradient problem that is common in standard RNNs. This architecture contains memory cells, which allow the network to retain information for lengthy periods, making it capable of capturing long-term data dependencies. LSTMs' unique gating mechanisms namely, the input, output, and forget gates enable the model to dynamically regulate the flow of information, determining what to remember, what to discard, and when to use the stored knowledge. This skill is especially useful in the highly volatile cryptocurrency market, where price fluctuations are impacted by a wide range of factors over varied periods. Using LSTMs, researchers can successfully describe the sequential patterns inherent in Dogecoin price changes, resulting in more accurate forecasts. The robustness of LSTMs in learning from prior data allows them to adapt to the unpredictable nature of cryptocurrency trading, making them a powerful tool for investors and analysts looking to understand and forecast Dogecoin price movements.

4.3 Data Visualization

In Fig 2, the graph illustrates Dogecoin's monthly price variations over a year, including the open, close, high, and low numbers. Prices remained largely consistent from January to June, with a little decrease in February (low of 9.57) followed by a steady rise. In July, there was a substantial increase, with the High price reaching 23.49, its highest point of the year. However, from August to December, prices progressively decreased, while they remained higher than earlier in the year, reaching a low of 13.41 in December. This points to a mid-year market rise followed by a decrease.

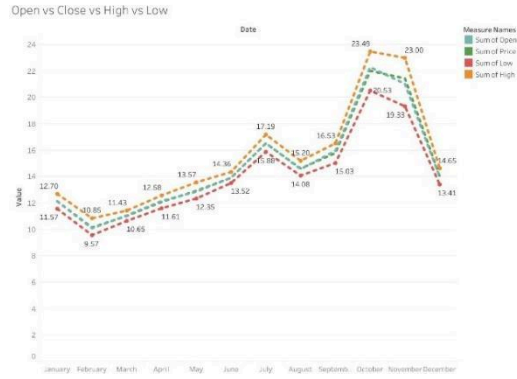


Fig 2. Data Visualization of Open vs Close vs High vs Low for year 2023

In Fig 3, The graph depicts Dogecoin's price from 2017 to 2024, with initial stability ranging between \$0.01 and \$0.1 until early 2021. A large spike occurred in 2021, with the price peaking at approximately \$0.7, driven by cryptocurrency market events, social media attention, and high-profile endorsements. Following this peak, the price fell dramatically before stabilizing. From 2022 to 2024, Dogecoin's price remained very stable, staying just over \$0, emphasizing the speculative nature of its 2021 boom and eventual market loss.

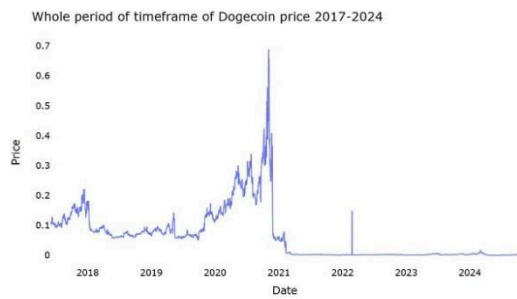


Fig 3. Data Visualization of the price over the period.

In Fig 4, the graph illustrates Dogecoin's monthly price variations over a year, including the open, close, high, and low numbers. Prices remained largely consistent from January to June, with a little decrease in February (low of 9.57) followed by a steady rise. In July, there was a substantial increase, with the High price reaching 23.49, its highest point of the year. However, from August to December, prices progressively decreased, while they remained higher than earlier in the year, reaching a low of 13.41 in December. This points to a mid-year market rise followed by a decrease.

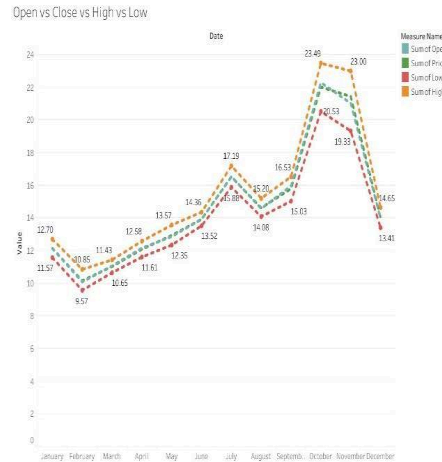


Fig 4. Data Visualization of Opens vs Close vs High vs Low for the Year 2023

4.4 Hyperparameter tuning

We performed substantial hyperparameter optimization to optimize the LSTM model's ability to predict Dogecoin pricing. The procedure began by comparing the performance of different optimizers, such as Adadelta, Adagrad, SGD, Adam, and Nadam, using Root Mean Square Error (RMSE) as the major assessment metric. Adam and Nadam had the lowest RMSE of the optimizers, and Adam was chosen because of his efficiency in generating the best R2 score and lowest prediction error.

Key hyperparameters were further tweaked to improve the model's performance. The final hyperparameter values are as follows:

Hyperparameter	Value Chosen
Optimizer	ADAM
Learning Rate	0.01
Epochs	50
Batch Size	32

Table 2. Hyperparameter tuning and it's values

Time series are typically used to forecast real values, a process known as regression. As a result, this paper's performance measurements concentrate on approaches for evaluating real-value predictions. The root-mean squared error (RMSE) is the most often used approach for measuring error in time series models. The root-mean-square error (RMSE) is a common measure of the discrepancies between values (sample values and projected values of a model).

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

5 Results

Two graphs show the performance of a trained and tested LSTM (Long Short-Term Memory) model for predicting Dogecoin prices after hyperparameter adjustment.

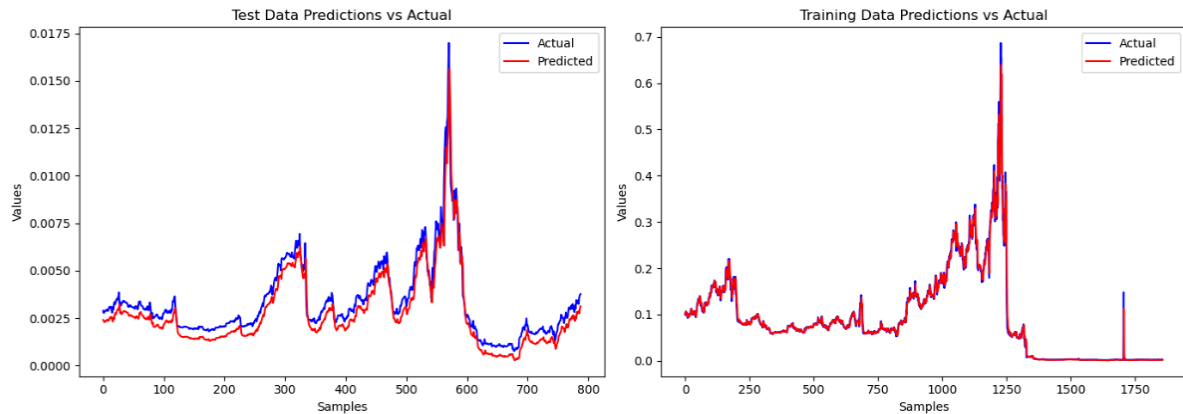


Fig 5. Test and Training Data vs Actual Prediction

The left plot, named "Test Data Predictions vs Actual," shows how effectively the LSTM model predicts Dogecoin prices using test data, which includes new, previously unseen price points. The blue line reflects current Dogecoin pricing, while the red line depicts anticipated values. The model's predictions closely track the trends in the actual data, with slight differences, showing good predictive ability. However, the model slightly underestimates some large spikes, such as the one around sample 600, indicating that the LSTM struggles to effectively capture high price volatility.

The right plot, "Training Data Predictions vs Actual," depicts the model's predictions for the training data, with real (blue) and anticipated (red) prices closely aligned. The high level of accuracy in the training set indicates that the LSTM model was well-fitted to Dogecoin's past price movements. However, tiny discrepancies in the peaks and valleys suggest that, while the model has learned to catch the major price patterns, it may still miss important features in sharp price fluctuations.

These charts show that the LSTM model performs well after hyperparameter adjustment, capturing general price trends and variations in Dogecoin prices throughout both the training and test datasets. However, some discrepancies on high volatility points in the test data indicate the possibility of further enhancements to better capture unexpected market spikes or decreases.

The study shows that an LSTM model trained on historical market data can forecast Dogecoin price movements with great accuracy. The model achieved an RMSE of 0.000651 and an R2 score of 0.894961 after hyperparameter optimization, which included using the Adam optimizer, learning at a rate of 0.01, 50 epochs, and a batch size of 32. The model accurately tracked general price trends on both the training and test datasets, as evidenced by the comparison of anticipated and actual values. However, certain inconsistencies emerged during periods of high volatility, notably fast price spikes, implying that the model could benefit from additional improvements to better capture these quick changes.

6 Conclusion

This research effectively shows the efficiency of an LSTM model for projecting Dogecoin prices based purely on past market data. The model produces solid predictions throughout steady market periods and moderately volatile situations, indicating that it is suitable for short- to medium-term forecasting. However, the study also indicates shortcomings in dealing with extreme price spikes caused by external market events, implying that adding more data, such as social mood or macroeconomic indicators, may improve the model's responsiveness in extremely volatile circumstances. Overall, this study establishes a solid foundation for bitcoin price prediction using LSTM, paving the door for future research into hybrid models to improve prediction accuracy in dynamic markets.

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