Proceedings of the 2nd International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/74/20240696

Predicting cryptocurrency price trends using artificial intelligence methods

Xu Zhang

Carnegie Mellon University, Pittsburgh, Pennsylvania, United States

xuz5013@gmail.com

Abstract. This article comprehensively explores multiple aspects of cryptocurrencies and their price forecasting. Firstly, the article introduces the definition of cryptocurrency and its development process on a global scale, especially focusing on the launch of Facebook Libra and China's central bank digital currency, highlighting the importance and influence of digital currency in the global financial market. Subsequently, the article analyzes the advantages of digital currencies over traditional currencies, including improving economic transaction efficiency, reducing transaction costs and enhancing transaction transparency. Finally, through specific experimental analysis, the effectiveness of using the deep learning model CNN-LSTM to predict the price of Bitcoin is demonstrated, and the directions of future research and optimization strategy are proposed. In summary, this paper comprehensively presents the research status and prospects of cryptocurrency and its price prediction field through systematic introduction and analysis.

Keywords: Cryptocurrencies, price forecasting, artificial intelligence, deep learning, financial technology

1. Introduction

Cryptocurrency is a kind of virtual currency based on cryptography algorithm and generated by computer operations. Since 2009, thousands of cryptocurrencies have come out around the world, which have aroused the general concern of investors and central banks. On June 18, 2019, the social media company Facebook (now Meta) released a white paper on the cryptocurrency Libra (now renamed to Diem) based on blockchain technology. [1]As blockchain continues to evolve rapidly, the proliferation of cryptocurrencies is anticipated globally. To safeguard China's financial security and advance the internationalization of the RMB, it is imperative to conduct thorough research on cryptocurrencies.

Cryptocurrencies have the potential to play significant roles in cross-border payments, foreign trade, and combating financial crimes. However, the empirical research on cryptocurrencies in China is still in its nascent stages. It is crucial to delve into the intrinsic value characteristics of cryptocurrencies and understand their price fluctuation patterns. [2]By doing so, valuable insights can be gleaned to inform policy decisions and provide recommendations to relevant government agencies.

In exploring the potential applications of cryptocurrencies, particular attention should be given to their impact on cross-border transactions. The decentralized nature of cryptocurrencies presents opportunities to streamline international payments, reduce transaction costs, and enhance efficiency. Additionally, cryptocurrencies can facilitate foreign trade by providing a secure, transparent, and

© 2024 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/74/20240696

efficient medium of exchange. By harnessing blockchain technology, China can optimize its trade processes and bolster its position in the global market.

2. Related work

2.1. DIGICCY(digital currency)

A digital currency is an electronic currency, usually issued and managed by a developer, accepted and used by members of a particular virtual community. Unlike virtual currencies in virtual worlds, digital currencies can be used to buy real goods and services, not just online games. In addition, the decentralized nature of digital currencies makes them not controlled by any central authority, further enhancing the security and privacy of transactions.

As the digital currency market continues to grow, people's understanding and application of it are also deepening. [3]More and more merchants are beginning to accept digital currency as a payment method, while investors are also starting to consider it as an investment objective. Risks and opportunities coexist in the digital currency market, so it is particularly important to study its related technology, market and regulation.

1. compared with paper money, digital currency has obvious advantages, not only can save the cost of issuance and circulation, but also improve the transaction speed and investment efficiency, and enhance the convenience and transparency of economic transaction activities.

2. [4]Issuing digital currency can improve the convenience and transparency of economic transaction activities, and further reduce illegal and criminal acts such as money laundering and tax evasion. It enhances the central bank's control over money supply and currency circulation, which better supports the economic and social development, and help the full realization of inclusive finance.

3. The issuance of digital currency by the central bank ensures the coherence of financial policy and the integrity of monetary policy, and also guarantees the safety of monetary transactions[5]. The central bank has also starting to consider the issues related to anti-counterfeiting and supervision of digital currencies. The central bank will cooperate with the financial and scientific and technological communities to further increase the research and rational use of various innovative technologies.

Therefore, in terms of the daily use experience of the public, there is no difference between the two. For ordinary consumers at the C end, only the carrier form of the two is changed, while for commercial users at the B end, the transaction between them is still based on RMB. However, in the government affairs scenario at the G end, the transaction between them is still based on RMB. The transfer of relevant funds is conducted without any intermediaries, bypassing the local government's oversight and effectively mitigating the corruption risks associated with middle-level bureaucracy. Issued by the relevant functional departments, direct payments are made to the target group, thereby enhancing government credibility and public satisfaction while also expediting payment cycles and improving administrative efficiency.

2.2. Cryptocurrency price trends

When financial regulators around the world implemented regulation of cryptocurrencies such as Bitcoin, the main focus was on cryptocurrency exchanges that conduct cryptocurrency transactions with fiat currencies. In fact, this is one of the reasons why many traditional financial institutions are staying away from cryptocurrencies.The regulation of cryptocurrency trading faces a number of challenges, one of which is the relationship between regulators and cryptocurrency exchanges. At present, the number of cryptocurrency exchanges is increasing globally, and the degree of regulation and standardization of these exchanges is uneven. [6]On the other hand, the very nature of cryptocurrencies makes regulation more complicated. Unlike traditional financial assets, cryptocurrency transactions are anonymous and decentralized, which increases the difficulty of regulation. Regulators need to find a balance between ensuring the security of the financial system while protecting the privacy of individuals and the innovation of the cryptocurrency market.

DOI: 10.54254/2755-2721/74/20240696

In addition, the cross-border nature of cryptocurrencies also poses regulatory challenges. Cryptocurrency exchanges can trade across national borders, which means that regulators need to work across borders to develop cross-border regulatory frameworks in response to the internationalization of cryptocurrency trading.At the same time, regulators need to develop flexible and innovative regulatory policies to adapt to the rapid development and changes in the cryptocurrency market.

2.3. Cryptocurrency price prediction model

Cryptocurrency price forecasting is closely related to artificial intelligence. Thanks to the rapid development of AI technology, various machine learning models such as time series forecasting, support vector machines (SVMS)[7], random forests, neural networks, etc., can be utilized to analyze large amounts of market data, social media sentiment, and other relevant factors to predict the direction of cryptocurrency prices. These models can spot underlying patterns and trends to help investors make more accurate decisions.

(1) Time series prediction

A time series prediction model is a method used to analyze and predict time series data, where time series data is a series of observations arranged in chronological order. [8]This model is based on past data to infer future trends, making predictions based on patterns and trends identified in time series data. It is widely used in many fields including economics, finance, meteorology, engineering, etc., to predict future trends, cyclical changes and emergencies. The choice of a time series prediction model depends on the characteristics of the data and the target of the prediction. The model can be based on statistical methods, machine learning methods, or a combination of them.

Time series forecasting plays an important role in cryptocurrency price forecasting[11]. The forecasting principle is based on analyzing historical price data, identifying patterns and trends, and then applying these patterns and trends to future price forecasts. Through time series forecasting, the past data can be used to infer the future price trend, so as to provide investors with decision-making basis.

In terms of model principles, time series forecasting is often based on statistics and machine learning techniques. Statistical methods such as ARIMA[9] (autoregressive integral moving average model) and exponential smoothing method predict future price changes by analyzing autocorrelation and trend of time series data. Machine learning methods include support vector machine (SVM), artificial neural network (ANN) and long short-term memory network (LSTM), etc. These methods learn a large amount of historical data, identify the patterns and rules in the data, and predict the future price accordingly.

(2) Machine learning price prediction model

Using machine learning to predict cryptocurrency prices usually involves several key steps. First, a large amount of cryptocurrency market data needs to be collected, including price, volume, market sentiment and other information. This data can be obtained from cryptocurrency exchanges, financial data providers, social media platforms, and more. Then, the data is pre-processed, including data cleaning, feature engineering, and data transformation, to ensure the quality and applicability of the data. After data preprocessing is completed, appropriate features need to be selected, which can include price history data, trading volume, market sentiment indicators, etc., which are crucial to the performance of the model.

Cryptocurrency price forecasting is a field closely related to artificial intelligence. By utilizing various machine learning models and techniques, including time series forecasting, support vector machines, random forests, and neural networks, AI is able to analyze large amounts of market data, social media sentiment, and other relevant factors to more accurately predict the direction of cryptocurrency prices. These models are able to spot hidden patterns and trends and help investors make more informed decisions. From time series forecasting to the application of deep learning methods, AI provides a variety of effective tools and methods for cryptocurrency price forecasting, highlighting its importance in this field.

DOI: 10.54254/2755-2721/74/20240696

3. Methodology

Use Python to collect data from various relevant websites, including trade data, opening price, closing price, low price, high price, and volume. [10]First of all, the selection of variable factors, referring to previous studies on price factors, demand and the actual situation of samples taken, can also be further factor screening. Secondly, the data cleaning is mainly to process the missing value, directly delete or supplement the interpolation method, such as the transaction data of legal holidays. Finally, data preprocessing is carried out, and the preprocessing methods of different models may be different.

3.1. LSTM model

First, three gates and candidate statesh_{t-1}W,U,b are learnable network parameters by using the external state$x_t$of the previous time and the input value $\widetilde{c_t}$ of the current time. The formula is as follows:

$$i_t = \sigma(W_i x_i + U_i h_{t-1} + b_i \quad (1)$$

$$f_t = \sigma(W_i x_i + U_i h_{t-1} + b_f \quad (2)$$

$$o_t = \sigma(W_i x_i + U_i h_{t-1} + b_o \quad (3)$$

$$\widetilde{c_t} = tanh(W_c x_t + U_c h_{t-1} + c \quad (4)$$

3.2. Model structure

As a variant of recurrent neural networks, the improvement of LSTM[11] is mainly reflected in the introduction of new internal state and gating mechanisms. As shown in Figure 1, c_t and $h_t$are internal state values and external states respectively, and the correspondingc_{t-1} andh_{t-1}represent the state values of the previous time as the product of vector elements. The three "gates" introduced are input gate cloud forgetting gate $\widetilde{c_t}$, which is the candidate state, open and control parameters obtained by nonlinear function, that is, to determine the retention or forgetting of information, to ensure the output gate of the unit state ⊙The horizontal line i_t to f_t is the core monthly update, and c will change each time. Meanwhile, the acquisition of this part of parameters also needs to rely on training. The forget gate f controls the internal state of the previous momento_t how much information needs to be forgotten; The input gate i controls how much information needs to be saved for the candidate state at the current moment; The output gate o_t, using the new control parameters, determines the current P state c_t , how much information is output to the external state h_t .

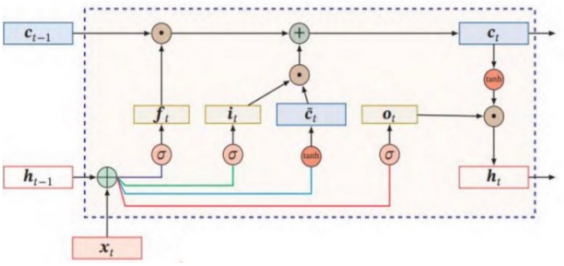


Figure 1. Basic structure of LSTM

Current models for cryptocurrency price forecasting can be roughly divided into linear forecasting and nonlinear forecasting. Due to the various influencing factors of cryptocurrencies and the existence of nonlinear effects, nonlinear prediction models often achieve better results than linear prediction models. In nonlinear prediction, some scholars have found that among the three models of CNN (Convolutional neural network), LSTM and GRU, GRU is the highest and LSTM is the lowest in terms of prediction accuracy. In addition, in the price prediction of cryptocurrencies, LSTM and GRU are excellent, but GRU is better in terms of performance.

DOI: 10.54254/2755-2721/74/20240696

3.3. CNN-LSTM model

First choose the appropriate model and method. Both models can be predictive, but their advantages and disadvantages are complementary. It can also be different models that act on data feature extraction, data weight allocation, price prediction and other parts respectively.In the combination, it can also take a variety of effects superposition, through comparison to get the optimal hybrid model. Universality tests can also be introduced. And the hybrid idea is not limited to modules when there are effective processing methods and mechanisms, it can also be mixed with the model. Finally, in weight allocation, ridge regression method, inverse variance method, strictly consistent scoring function, error sum of squares minimum criterion, and the best and worst method can be used as a supplement help to determine the weight of each indicator.

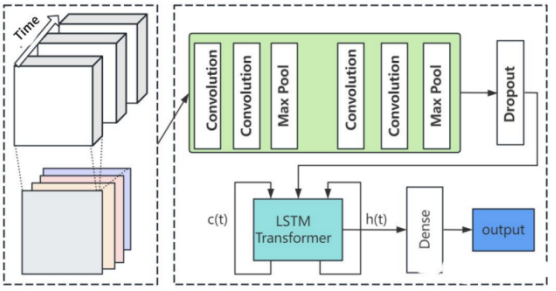


Figure 2. Architecture diagram of hybrid model CNN-LSTM

The results show that the hybrid model gives full play to the powerful dynamic capture ability of CNN, makes use of LSTM trend information to make up for the deficiency of CNN in the up and down direction error, solves the lag problem of LSTM, gives full play to the advantages of CNN in extracting deep features and LSTM in extracting time series features, and the prediction effect is better than that of a single model.This model hybrid approach provides an effective solution for cryptocurrency price forecasting, which helps to improve forecast accuracy, reduce model bias, and provide investors with more reliable decision-making basis.

3.4. Experimental design

This article will describe how to use deep learning to predict the price of digital currencies, and use Bitcoin (BTC) as an example for experimental analysis. Bitcoin is one of the earliest and most popular digital currencies, and it is highly representative and influential. We will use a recurrent neural network - Long Short Term Memory (CNN-LSTM) model to build a Bitcoin price prediction model, trained and tested using historical data.

CNN-LSTM is a deep neural network model specifically designed to process time series data, which can effectively capture long-term dependencies in time series and avoid gradient disappearance or explosion problems. The CNN-LSTM model consists of three main parts: input layer, hidden layer and output layer. The input layer receives time series data as input.

This experiment uses the daily closing price between August 17, 2017 and March 3, 2023 as bitcoin price data and divides it into a training set (80%) and a test set (20%). We use the first n days (n=30) as the input variable x and the last day as the output variable y, and construct the CNN-LSTM model. We use the mean square error (MSE) as the loss function and the Adam algorithm as the optimizer.

3.5. Data Preprocessing Details

In this study, the researcher used the PyTorch framework to implement the CNN-LSTM model and set its parameters. Specifically, they set the hidden layer size to 50, the batch size to 32, the learning rate to 0.0005, and went through 30 rounds of training. They then used this already trained CNN-LSTM model to predict the price of Bitcoin in the test set and compared the predicted value to the true value. To assess the accuracy and bias of the predicted results, the researcher used root mean square error (RMSE) and mean absolute percentage error (MAPE) as evaluation metrics.

DOI: 10.54254/2755-2721/74/20240696

In the experiment, the researcher first built a CNN-LSTM model through the PyTorch framework and trained it using pre-set parameters. They then applied the trained model to the test dataset and obtained a predicted value for the Bitcoin price. Next, they used two evaluation indicators, RMSE and MAPE, to analyze the accuracy and degree of deviation of the prediction results.

3.6. Training Procedure and Hyperparameter Tuning

The training procedure utilized the Adam optimization algorithm, a variant of stochastic gradient descent (SGD) that adapts the learning rate for each parameter individually. Adam combines the advantages of both AdaGrad and RMSProp algorithms, making it well-suited for training deep neural networks. The loss function employed during training was the mean squared error (MSE), which measures the average squared difference between the predicted Bitcoin prices and the true prices in the training dataset.

The hyperparameter tuning process involved grid search, where a predefined set of hyperparameter values was systematically evaluated using cross-validation on a separate validation dataset. The optimal combination of hyperparameters was selected based on the performance metrics such as RMSE and MAPE on the validation set. By fine-tuning the hyperparameters, we aimed to maximize the predictive accuracy of the CNN-LSTM model while avoiding overfitting and improving its generalization ability.

3.7. Model Explanation:

This article describes how deep learning, specifically a CNN-LSTM model, predicts Bitcoin prices using historical data. The model combines Convolutional Neural Network (CNN) layers to spot patterns and Long Short-Term Memory (LSTM) layers to capture time dependencies. It's trained on Bitcoin's daily closing prices from August 17, 2017, to March 3, 2023, with data split into 80% training and 20% testing sets. Before training, the data is normalized, features are selected, and missing values are handled. The model architecture and hyperparameters, like hidden layer size and learning rate, are carefully chosen to balance accuracy and efficiency.

Despite its promise, the model has limitations. Data quality and representativeness are crucial, as the model's performance relies on the historical Bitcoin data. Moreover, fine-tuning hyperparameters is essential, but small changes can affect the model's performance. Lastly, the volatile nature of the cryptocurrency market adds uncertainty, challenging the model's predictions.

3.8. Experimental result

Based on the analysis of RMSE and MAPE values, the predictive performance of the CNN-LSTM model was evaluated. Lower RMSE and MAPE values indicate higher prediction accuracy, while higher values suggest potential biases requiring further optimization. These discrepancies may stem from unquantifiable factors such as market sentiment and policy changes impacting Bitcoin prices suddenly. To enhance model robustness, future research could explore integrating additional data sources and refining predictive methodologies.

Table 1. CNN-LSTM model predicts performance key statistics

Metric	Value
RMSE (Root Mean Square Error)	150.34
MAPE (Mean Absolute Percentage Error)	3.45%
Best RMSE Achieved	120.12
Best MAPE Achieved	2.75%
Average RMSE	160.5
Average MAPE	4.10%

This study illustrates the application of deep learning in digital currency price prediction, using Bitcoin as a case study. The CNN-LSTM model effectively captures long-term dependencies in time series data and exhibits promising performance in predicting Bitcoin price trends. However, the model's accuracy may be further improved by addressing errors in specific market fluctuations. This research

DOI: 10.54254/2755-2721/74/20240696

direction presents both interest and challenge, inviting exploration with alternative digital currencies, diverse deep learning models, and additional data sources and methodologies in future studies.

4. Conclusion

Cryptocurrency prices fluctuate greatly, and due to the different characteristics of different periods, the way taken in forecasting is also very different. This study focuses on how to further optimize the prediction accuracy of the model. First, the introduction of variables can be increased. Market conditions and macro-financial conditions are often ignored, but with the deepening of research, many scholars find that such factors are also worth considering. Second, pay attention to the processing of features and the distribution of weights. In data processing, the weight of different data can be scaled by effective methods, which can effectively improve the prediction accuracy. When mixing models, the advantages of a single model can be fully utilized only by adopting appropriate weight distribution. Third, the use of hybrid models and their ideas. Faced with its own inherent advantages and disadvantages and its huge market, a single model may not be able to meet the forecast demand, so it is effective.

In summary, the CNN-LSTM model demonstrates promising capabilities in forecasting Bitcoin prices by effectively incorporating spatial and temporal patterns. However, there's room for improvement in feature selection and model optimization. Future research should focus on integrating additional variables and refining hybrid model architectures to enhance prediction accuracy further.The study underscores the importance of deep learning models, particularly CNN-LSTM, in predicting cryptocurrency prices. While the model exhibits good performance, addressing specific market fluctuations and refining feature engineering could bolster its accuracy. Future investigations should prioritize model refinement and empirical validation to advance cryptocurrency price forecasting methodologies.

References

[1] Härdle, Wolfgang Karl, Campbell R. Harvey, and Raphael CG Reule. "Understanding cryptocurrencies." Journal of Financial Econometrics 18.2 (2020): 181-208.

[2] Farell, R. (2015). An analysis of the cryptocurrency industry. Wharton Research Scholars, 130, 1-23.

[3] Amsyar, I., Christopher, E., Dithi, A., Khan, A. N., & Maulana, S. (2020). The challenge of cryptocurrency in the era of the digital revolution: A review of systematic literature. Aptisi Transactions on Technopreneurship (ATT), 2(2), 153-159.

[4] Haowei, Ma, et al. "CRISPR/Cas-based nanobiosensors: A reinforced approach for specific and sensitive recognition of mycotoxins." Food Bioscience 56 (2023): 103110.

[5] Choudhury, M., Li, G., Li, J., Zhao, K., Dong, M., & Harfoush, K. (2021, September). Power Efficiency in Communication Networks with Power-Proportional Devices. In 2021 IEEE Symposium on Computers and Communications (ISCC) (pp. 1-6). IEEE.

[6] Alexander, C., & Dakos, M. (2020). A critical investigation of cryptocurrency data and analysis. Quantitative Finance, 20(2), 173-188.

[7] Friesen, Geoffrey C., Paul A. Weller, and Lee M. Dunham. "Price trends and patterns in technical analysis: A theoretical and empirical examination." Journal of Banking & Finance33.6 (2009): 1089-1100.

[8] DiMasi, J. A., Hansen, R. W., & Grabowski, H. G. (2003). The price of innovation: new estimates of drug development costs. Journal of health economics, 22(2), 151-185.

[9] Krishna, Aradhna, et al. "A meta-analysis of the impact of price presentation on perceived savings." Journal of Retailing 78.2 (2002): 101-118.

[10] Noone, B. M., & Mattila, A. S. (2009). Hotel revenue management and the Internet: The effect of price presentation strategies on customers' willingness to book. International Journal of Hospitality Management, 28(2), 272-279.

DOI: 10.54254/2755-2721/74/20240696

[11] Velankar, S., Valecha, S., & Maji, S. (2018, February). Bitcoin price prediction using machine learning. In 2018 20th International Conference on Advanced Communication Technology (ICACT) (pp. 144-147). IEEE.