International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 05 | May - 2023 Impact Factor: 8.176 ISSN: 2582-3930

CRYPTOCURRENCY PRICE ANALYSIS WITH ARTIFICIAL INTELLIGENCE

[1]SOWMIYA S R, [2]RAJESH P, [3]HANISH P, [4]ABUSYEED SK, [5]VAMSI KRISHNA V

[1]Faculty of Computer Science & Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur. [2]Computer Science & Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur. [3]Computer Science & Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur. [4]Computer Science & Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur. [5]Computer Science & Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur.

ABSTRACT: Crypto currency is playing an increasingly important role in reshaping the financial system due to its growing popular appeal and mechant acceptance. While many people are making investments in Cryptocurrency, the dynamical features, uncertainty, the predictability of Cryptocurrency are still mostly unknown, which dramatically risk the investments. It is a matter to try to understand the factors that infiuence the value formation. In this study, we use advanced artificial intelligence frameworks of fully connected Artificial Neural Network (ANN) and Long Short Term Memory (LSTM) Recurrent Neural Network to analyse the price dynamics of Bitcoin, Etherum, and Ripple. We find that ANN tends to rely more on long-term history while LSTM tends to rely more on short-term dynamics, which indicate the efficiency of LSTM to utilise useful information hidden in historical memory is stronger than ANN. However, given enough historical information ANN can achieve a similar accuracy, compared with LSTM. This study provides a unique demonstration that Cryptocurrency market price is predictable. However, the explanation of the predictability could vary depending on the nature of the involved machine-learning model.

KEYWORDS: Cryptocurrancy , Artificial Neural Network (ANN), Long Short Term Memory (LSTM).

I INTRODUCTION

Cryptocurrency is the peer-to-peer digital moneyory and payment system that exist online via a controlled algorithem. When a miner cracks an algorithem to record a block of transactions to public ledger named blockchain and the cryptocurrency is created when the block is added to the blockchain. It allows people to store and transfer through encryption protocol and distributed network. Mining is a necessary and competitive component of the cryptocurrency system. The miner with more computational power has a better chance of finding a new coin than that of less. Bitcoin is the first and one of the leading digital currencies (its market capitalisation had more than $ 7 billion in 2014, and then it increased significantly to $ 29 billion in 2017) which was first introduced by Satoshi Nakamoto in 2008. Among many features of bitcoin, the most impressive one is decentralisation that it can remove the involvement of traditional financial sectors and monetary authorities effectively due to its blockchain network features . In addition, the electronic payment system of Bitcoin is based on cryptographic proof rather than the trust between each other as its transaction history cannot be changed unless redoing all proof of work of all blockchain, which play a critical role of being a trust intermediary and this can be widely used in reality such as recording charitable contribution

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 05 | May - 2023 Impact Factor: 8.176 ISSN: 2582-3930

to avoid corruption. Moreover, bitcoin has introduced the controllable anonymity scheme, and this enhances users' safety and anonymity by using this technology, for instance, we can take advantage of this property of blockchain to make identification cards, and it not only can protect our privacy but verify our identity. Nowadays, investing in cryptocurrencies, like Bitcoin, is one of the efficient ways of earning money. For example, the rate of Bitcoin significant rises in 2017, from a relatively low point 963 USD on January 1ST 2017, to its peak 19186 USD on December 17th 2017, and it closed with 9475 USD at the end of the year. Consequently, the rate of return of bitcoin investment for 2017 was over 880%, which is an impressive and surprising scenery for most investors. While an increasing number of people are making investments in Cryptocurrency, the majority of investors cannot get such profit for being inconsiderable to cryptocurrencies' dynamics and the critical factors that influence the trends of bitcoins. Therefore, raising people's awareness of vital factors can help us to be wise investors. Although market prediction is demanding for its complex nature the dynamics are predictable and understandable to some degree. For example, when there is a shortage of the bitcoin, its price will be increased by their sellers as investors who regard bitcoin as a profitable investment opportunity will have a strong desire to pay for bitcoin. Furthermore, the price of bitcoin may be easily influenced by some 2 influential external factors such as political factors . Although existing efforts on Cryptocurrency analysis and prediction is limited, a few studies have been aiming to understand the Cryptocurrency time series and build statistical models to reproduce and predict price dynamics. For example, Madan et al. collected bitcoins price with the time interval of 0.5, 1and 2 hours, and combined it with the blockchain network, the underlying technology of bitcoin. Their predictive model leveraging random forests and binomial logistic regression classifiers , and the precision of the model is around 55% in predicting bitcoin's price.

Shah et al. used Bayesian regression and took advantages of high frequency (10-second) prices data of Bitcoin to improve investment strategy of bitcoin . Their models had also achieved great success.

In an Multi-Layer Perceptron (MLP) based prediction model was presented to forecast the next day price of bitcoin by using two sets of input: the first type of inputs: the opening, minimum, maximum and closing price and the second set of inputs: Moving Average of both short (5,10,20 days) and long (100, 200 days) windows. During validation, their model was proved to be accurate at the 95% level. There has been many academic researches looking at exchang rate forecasting, for example, the monetary and portfolio balance models examined by Meese and Rogoff (1983, 1988) . Significant efforts have been made to analyse and predict the trends of traditional financial markets especially the stock market however, predicting cryptocurrencies market prices is still at an early stage. Compared to these stock price prediction models, traditional time series methods are not very useful as cryptocurrencies are not precisely the same with stocks but can be deemed as a complementary good of existing currency system with sharp fluctuations features. Therefore, it is urgently needed to understand the dynamics of cryptocurrencies better and establish a suitable predictive modelling framework. In this study, we hypothesis that time series of cryptocurrencies exhibits a clear internal memory, which could be used to help the memorybased time series model to works more appropriately if the length of internal memory could be quantified. We aim to use two artificial intelligence modelling frameworks to understand and predict the most popular cryptocurrencies price dynamics, including Bitcoin, Ethereum, and Ripple

II DATASET DESCRIPTION

The data was taken from an open-source repository Kaggle and also collected manually. The dataset contains nearly 30,000 public data of bitcoin price and money transactions.

III PROPOSED MODEL

Among many features of bitcoin, the most impressive one is decentralisation that it can remove the involvement of traditional financial sectors and monetary authorities effectively due to its blockchain network features. In addition, the electronic payment system of Bitcoin is based on cryptographic proof rather than the trust between each other as its transaction history cannot be changed unless redoing all proof of work of all blockchain, which play a critical role of being a trust intermediary and this can be widely used in reality such as recording charitable contribution to avoid corruption.

IV RELATED WORK

In recent years there has been tremendous research done on Cryptocurrency price analysis. With the help of a literature survey we, realized the basic steps in Cryptocurrency price analysis are:

- **Data Collection:** This module involves collecting historical and real-time data on cryptocurrency prices, trading volumes, market capitalization, and other relevant metrics.

- **Data Cleaning and Preprocessing:** The data collected may need to be cleaned, processed, and transformed to be used effectively by the machine learning algorithms.

- **Feature Extraction:** This module involves selecting the most relevant features from the data collected and extracting them in a format suitable for use by the machine learning algorithms.

- **Machine Learning:** This module involves training machine learning algorithms to recognize patterns in the data that correlate with future price movements. Various techniques like deep learning, reinforcement learning, and time-series analysis can be used to train these algorithms.

- **Model Evaluation:** Once the models have been trained, they need to be evaluated to assess their performance on test data. This module helps to determine the accuracy and reliability of the models.

- **Predictive Modeling:** This module involves using the trained models to make predictions about future price movements based on new data.

- **Visualization:** This module involves creating visual representations of the data and model predictions, allowing traders and investors to easily interpret and understand the results.

- **Deployment:** Finally, the models and visualizations need to be deployed in a system that can be accessed by traders and investors. This module may involve building web-based dashboards, APIs, or other software tools to make the predictions and visualizations available to the users.

V METHODOLOGY & APPROACH

In this project we aimed to improve the accuracy by using the following algorithms.

- **Artificial Neural Network (ANN):**
  In cryptocurrency price analysis, ANNs can be trained to recognize patterns in historical price data and use those patterns to predict future price movements. Deep learning neural networks, in particular, have been shown to be highly effective in analyzing and predicting cryptocurrency prices due to their ability to learn complex nonlinear relationships in data.

  To use LSTMs for cryptocurrency price analysis, the following steps may be involved:

  1.**Data collection:** Collect historical and real-time data on cryptocurrency prices, trading volumes, market capitalization, and other relevant metrics.

  2.**Data preprocessing:** Clean and preprocess the data to make it suitable for use in training the LSTM.

  3.**Feature selection:** Select the most relevant features from the data, such as price trends, trading volumes, market sentiment, and technical indicators.

  4.**LSTM architecture design:** Choose an appropriate LSTM architecture, including the number of layers, number of neurons per layer, and activation functions.

  5.**Training the LSTM:** Use the selected data to train the LSTM, adjusting the internal parameters to optimize the performance of the network.

  6.**Testing and validation:** Validate the performance of the LSTM on a separate test dataset to ensure that it can accurately predict future prices.

  7. **Deployment:** Deploy the trained LSTM in a system that can be accessed by traders and investors to make predictions about future cryptocurrency prices.

- **Long Short-Term Memory (LSTM):** Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is commonly used in cryptocurrency price analysis with artificial intelligence (AI). LSTMs are designed to overcome the limitations of traditional RNNs by being able to handle long-term dependencies in time series data. In cryptocurrency price analysis, LSTMs can be used to analyze historical price data and make predictions about future price movements. LSTMs can capture long-term trends in the data while still being able to respond quickly to changes in market conditions, making them well-suited for analyzing the highly dynamic cryptocurrency market.
  Overall, LSTMs are a powerful tool for cryptocurrency price analysis with AI, enabling traders and investors to make informed decisions based on accurate predictions of future price movements.Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN)

VI CONCLUSION

Cryptocurrency, such as Bitcoin, has established itself as the leading role of decentralisation. There are a large number of cryptocurrencies sprang up after Bitcoin such as Ethereum and Ripple. Because of the significant uncertainty in its prices, many people hold them as a means of speculation. Therefore, it is critically important to understand the internal features and predictability of those cryptocurrencies. In this study, we use two distinct artificial intelligence frameworks, namely, fully-connected Artificial Neural Network (ANN) and Long-Short-Term-Memory (LSTM) to analyse and predict the price dynamics of Bitcoin, Etherum, and Ripple. We showed that the ANN and LSTM models are comparable and both reasonably well enough in price prediction, although the internal structures are different. Then we further analyse the influence of historical memory on model prediction. We find that ANN tends to rely more on longterm history while LSTM tends to rely more on short-term dynamics, which indicate the efficiency of LSTM to utilise useful information hidden in historical memory is stronger than ANN. However, given enough historical information ANN can achieve a similar accuracy, compared with LSTM. This study provides a unique demonstration that Cryptocurrency market price is predictable. However, the explanation of the predictability could vary depending on the nature of the involved machine-learning model.

VII FUTURE ENHANCEMENT

For the future work, There are several potential future enhancements that can be made to improve the effectiveness of cryptocurrency price analysis with artificial intelligence (AI). Here are a few possible like Incorporating additional data sources, Multi-modal learning, Ensemble learning, Reinforcement learning and Explainable AI.

VIII REFERENCES

[1] Adebiyi AA, Ayo C K, Adebiyi MO, Otokiti SO. Stock price prediction using a neuralnetwork with hybridized market indicators. Journal of Emerging Trends in Computingand InformationSciences, 2012,3(1):1-9.

[2]Advances in Neural Information Processing Systems, 2014.

[3]AriyoAA,AdewumiAO,AyoCK.StockpricepredictionusingtheARIMAmodel.InUKSim-AMSS16thIEEEInternationalConferenceonComputerModellingandSimulation (UKSim),2014,pp.106-112

[4]Bresler G, Chen G.H, and Shah.D, "A latent source model for online collaborative filtering," in

[5]Chen G.H, Nikolov .S, and Shah .D, "A latent source model for nonparametric time series classification," in Advances in Neural Information Processing Systems, pp. 1088–1096, 2013.

[6]Cheung,Y.W.,Chinn,M.D.,&Pascual,A.G.(2005).Empiricalexchangeratemodelsofthenineties:A reanyfittosurvive?.Journalofinternationalmoneyandfinance,24(7),1150-1175.

[7]Greaves,A.,&Au,B.(2015).Usingthebitcointransactiongraphtopredictthepriceofbitcoin. No Data.

[8]Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to acost of production model for valuing bitcoin. Telematics and Informatics, 34(7), 1308-1321.

[9]IndraNI, YassinIM, ZabidiA, RizmanZI. Non linear auto regressive with exogenous input (mrx) bitcoin price prediction model using so- optimized parameters and moving average technical indicators . J.Fundam.Appl.Sci.,2017,9(3S),791-808`.

[10]Jay .P, Kalariya .V, Parmar .P, Tanwar

.S, Kumar .N, and Alazab .M, ‘‘Stochastic neural networks for cryptocurrency price prediction,’’ IEEE Access, vol. 8, pp. 82804–82818,2020.

[11]KaastraandM.Boyd,“Designinganeuralnetworkforforecastingfinancialandeconomictimeseries,” Neurocomputing,vol.10,no.3,pp.215–236,1996.

[12]Kim .J, Kim .S, Wimmer .H, and Liu .H, ‘‘A cryptocurrency prediction model using LSTM and GRU algorithms,’’ in Proc. IEEE/ACIS 6th Int. Conf. Big Data, Cloud Comput., Data Sci. (BCD), Sep. 2021, pp. 37–44.

[13]Lamon .C, Nielsen .E, and Redondo .E, ‘‘Cryptocurrency price prediction using news and social media sentiment,’’ SMU Data Sci. Rev., vol. 1, no. 3, pp. 1–22, 2017.

[14]Nakamoto.S (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. Cryptography Mailing List. [Online]. Available: https://metzdowd.com

[15]Ron, D., & Shamir, A. (2013, April). Quantitative analysis of the full bitcoin transactiongraph. In International Conference on Financial Cryptography and Data Security (pp. 6-24). Springer, Berlin,Heidelberg.

[16]Shah,D.,&Zhang,K.(2014,September).BayesianregressionandBitcoin.InCommunication,Control,andComputing(Allerton),201452ndAnnual AllertonConferenceon(pp. 409-414).IEEE.

[17]Sheth .K, Patel .K, Shah .H, Tanwar .S, Gupta .R, and Kumar .N, ‘‘A taxonomy of AI techniques for 6G communication networks,’’ Comput. Commun., vol. 161, pp. 279–303, Sep. 2020

[18]Sharma.R (2019). Do Bitcoin Mining Energy Costs Influence its Price? Accessed: 2019. [Online]. Available: https://www.investopedia. com/news/do-bitcoin-mining-energy-costs-influence-its-price/.

[19]Valencia .F, Gómez-Espinosa .A, and Valdés-Aguirre .B, ‘‘Price movement prediction of cryptocurrencies using sentiment analysis and machine learning,’’ Entropy, vol. 21, no. 6, p. 589, Jun. 2019

[20]WhiteH.,“Economicpredictionusingneuralnetworks:Thecaseofibmdailystockreturns,”in Neural Networks,1988.,IEEEInternationalConferenceon.IEEE,1988,pp.451–458