International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

A MACHINE LEARNING MODELING FOR BITCOIN MARKET PRICE PREDICTION BASED ON THE LONG SHORT-TERM MEMORY RECURRENT NEURAL NETWORK

[1]B Hari Kumar, [2]Musa Om Prakash , [3]Amulya Koppula, [4]Athikam Akhila
[123]Assistanct Professor, [4]UG Scholar, Department of CSE, Brilliant Institute of Engineering & Technology, Abdullapurmet(V&M) Ranga Reddy Dist-501505

ABSTRACT

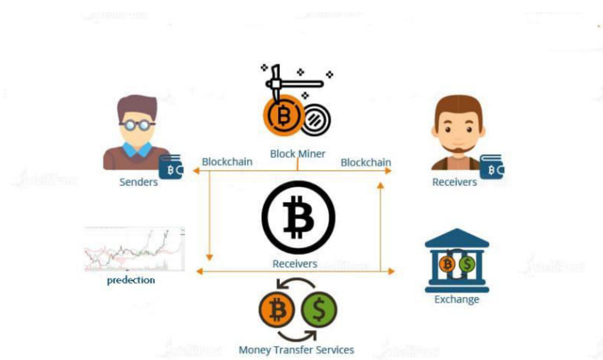
Cryptocurrency is playing an increasingly important role in reshaping the financial system due to its growing popular appeal and mechant acceptance. While many people are making investments in Cryptocurrency, the dynamical features, uncertainty, the predictability of Cryptocurrency are still mostly unknown, 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.

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 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 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

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

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 hypothesise that time series of cryptocurrencies exhibits a clear internal memory, which could be used to help the memory-based 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.EXISTING SYSTEMS

Existing systems for Bitcoin market price prediction typically employ a range of statistical and machine learning techniques. Traditional methods such as moving averages, autoregressive integrated moving average (ARIMA) models, and linear regression have been used to forecast Bitcoin prices based on historical price data and trading volumes. For example, ARIMA models capture temporal dependencies and trends in the time series data, while moving averages smooth out short-term fluctuations to identify long-term trends [1].

However, these traditional approaches have notable limitations. They often fail to capture the complex, non-linear patterns and long-term dependencies inherent in Bitcoin price movements. For instance, linear models like ARIMA assume a constant relationship between variables over time, which does not adequately address the volatility and sudden shifts in the cryptocurrency market [2]. Additionally, traditional methods generally require extensive feature engineering and may not perform well in the face of highly volatile or rapidly changing market conditions [3].

Moreover, many existing systems rely on static features and do not fully leverage the temporal dynamics of financial time series. This can lead to suboptimal predictions, as these systems may not adapt to new patterns or trends in the data. For instance, traditional models might struggle with incorporating recent market events or sentiment shifts into their predictions, resulting in less accurate forecasts [4].

III.PROPOSED SYSTEM

The proposed system utilizes Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs) to improve Bitcoin market price prediction. LSTM networks are well-suited for modeling time series data due to their ability to capture long-term dependencies and patterns over time. Unlike traditional methods, LSTMs have built-in mechanisms to handle and remember long-term relationships within the data, making them particularly effective for financial market predictions where past events influence future prices [5].

The proposed system integrates LSTM networks to model the temporal dynamics of Bitcoin prices, leveraging both historical price data and other relevant features such as trading volume, market sentiment, and macroeconomic indicators. By employing LSTM networks, the system can better capture complex non-linear relationships and adapt to changing market conditions. This approach offers several advantages:

1. **Enhanced Accuracy:** LSTMs can handle long-term dependencies and capture intricate patterns in time series data, leading to more accurate predictions compared to traditional models [6].
2. **Dynamic Adaptation:** The system can dynamically adapt to new data and market trends, improving its responsiveness to sudden changes or anomalies in the Bitcoin market [7].
3. **Feature Integration:** LSTMs can effectively integrate multiple features, such as market sentiment and trading volume, to enhance the prediction accuracy and provide a more comprehensive view of market dynamics [8].
4. **Reduced Need for Feature Engineering:** LSTM networks can learn complex patterns directly from raw data, reducing the need for extensive feature engineering and enabling more straightforward model development

IV.MODULES

- User
- Agent
- admin
- artificial intelligence

User

Registration of User details next admin activated by the user. go to user page and login. User view some fields [start trading, bit bucket, prediction, logout] now open start treding page contains sale available cryptocurrencies and user buy the currency.user views the transaction history details and user view the prediction for available datasets.

Agent

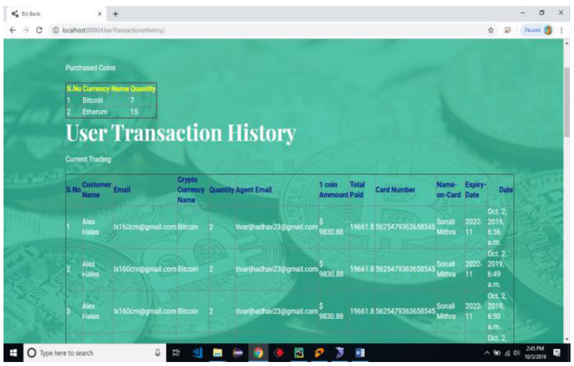
First registration of the agent page. next activated by the admin. Login agent page. agent view some fields[buy, bitbucket, block bucket, prediction, logout]. here three types of digital currency's are there [bitcoins, ripple, Etherum] agent can buy digital currency (any one or all three).Agent buying the crypto currency. agent transaction history also available.

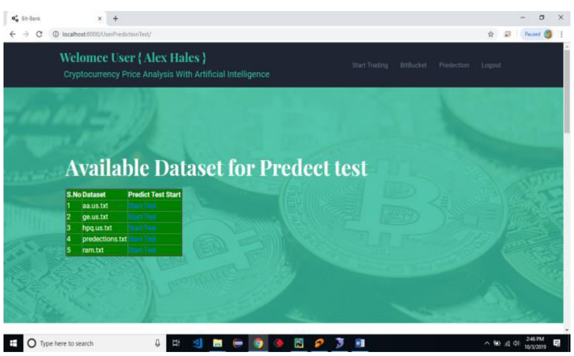
Admin

The aim of admin is to approve the users and agents .admin contains some fields[user,agents,crypto,bitblock].admin view user and agent registered details and in crypto field user update the currecy rate and view the recently crypto currency changes list.admin view the current transaction details. 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

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

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.





Artificial intelligence

The application of advanced digital, smart technologies, robotic systems, new materials and design techniques, creation of large data processing systems, computer-aided learning and artificial intelligence (AI) are relevant for various branches of science and technology, including manned space programs. Some technology concepts and pilot systems based on the AI (3-D computer vision, automated systems for planning and evaluating the activities of cosmonauts, inquiry and communications system) were developed in the industry over several decades .

V.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 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.

VI.REFERENCES

[1] Greaves, A., & Au, B. (2015). Using the bitcoin transaction graph to predict the price of bitcoin. No Data.

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

[3] Shah, D., & Zhang, K. (2014, September). Bayesian regression and Bitcoin. In Communication, Control, and Computing (Allerton), 2014 52nd Annual Allerton Conference on (pp. 409-414). IEEE.

[4] Indra N I, Yassin I M, Zabidi A, Rizman Z I. Non-linear autoregressive 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`

[5] Adebiyi AA, Ayo C K, Adebiyi MO, Otokiti SO. Stock price prediction using a neural network with hybridized market indicators. Journal of Emerging Trends in Computing and Information Sciences, 2012, 3(1):1-9

[6] Adebiyi AA, Ayo C K, Adebiyi MO, Otokiti SO. Stock price prediction using a neural network with hybridized market indicators. Journal of Emerging Trends in Computing and Information Sciences, 2012, 3(1):1-9

[7] Ariyo AA, Adewumi AO, Ayo CK. Stock price prediction using the ARIMA model. In UKSim-AMSS 16th IEEE International Conference on Computer Modelling and Simulation (UKSim), 2014, pp. 106-112

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

[9] H. White, "Economic prediction using neural networks: The case of ibm daily stock returns," in Neural Networks, 1988., IEEE International Conference on. IEEE, 1988, pp. 451–458

[10] Kaastra and M. Boyd, "Designing a neural network for forecasting financial and economic time series," Neurocomputing, vol. 10, no. 3, pp. 215–236, 1996.

[11] H. White, "Economic prediction using neural networks: The case of ibm daily stock returns," in Neural Networks, 1988., IEEE International Conference on. IEEE, 1988, pp. 451–458 .

[12] Cheung, Y. W., Chinn, M. D., & Pascual, A. G. (2005). Empirical exchange rate models of the nineties: Are any fit to survive?. Journal of international money and finance, 24(7), 1150-1175.