Crypto Currency Price Analysis With Artificial Intelligence

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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.

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 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.

LITERATURE SURVEY

1) Using the Bitcoin Transaction Graph to Predict the Price of Bitcoin

AUTHORS: Greaves, A., & Au, B.

with different objectives. A pre-defined set of minimum qualification

levels should be distributed between the crew members with minimum

training time differences, training expenses or a maximum of the train-

ing level with a limitation of the budget.

First, a description of the cosmonaut training process is given.

Then four models are considered for the volume planning problem.

The objective of the first model is to minimize the differences between

the total time of the preparation of all crew members, the objective of

the second one is to minimize the training expenses with a limitation of

the training level, and the objective of the third one is to maximize the training level with a limited budget. The fourth model considers the

problem as an n-partition problem. Then two models are considered

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We consider the problem of planning the ISS cosmonaut training

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Bitcoin is the world's leading cryptocurrency, allowing users to make transactions securely and anonymously over the Internet. In recent years, The Bitcoin the ecosystem has gained the attention of consumers, businesses, investors and speculators alike. While there has been significant research done to analyze the network topology of the Bitcoin network, limited research has been performed to analyze the network's influence on overall Bitcoin price. In this paper, we investigate the predictive power of blockchain network-based features on the future price of Bitcoin. As a result of blockchain-networkbased feature engineering and machine learning optimization, we obtain up-down Bitcoin price movement classification accuracy of roughly 55%.

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For the volume planning problem, two algorithms are presented.

The first one is a heuristic with a complexity of (n)operations. The

second one consists of a heuristic and exact parts, and it is based on

the n-partition problem appro

2) CRYPTOCURRENCY VALUE FORMATION: AN EMPIRICAL ANALYSIS LEADING TO A COST OF PRODUCTION MODEL FOR VALUING BITCOIN

AUTHORS: Hayes, A. S.

This paper aims to identify the likely source(s) of value that cryptocurrencies exhibit in the marketplace using cross sectional empirical data examining 66 of the most used such 'coins'. A regression model was estimated that points to three main drivers of cryptocurrency value: the difficulty in 'mining 'for coins; the rate of unit production; and the cryptographic algorithm employed. These amount to relative differences in the cost of production of one coin over another at the margin, holding all else equal. Bitcoin-denominated relative prices were used, avoiding much of the price volatility associated with the dollar exchange rate. The resulting regression model can be used to better understand the drivers of relative value observed in the emergent area of cryptocurrencies. Using the above analysis, a cost of production model is proposed for valuing bitcoin, where the primary input is electricity. This theoretical model produces useful results for both an individual producer, by setting breakeven points to start and stop production, and for the bitcoin exchange rate on a macro level. Bitcoin production seems to resemble a competitive commodity market; in theory miners will produce until their marginal costs equal their marginal product.

3. Economic prediction using neural networks: the case of IBM daily stock returns

AUTHORS: H. White

A report is presented of some results of an ongoing project using neural-network modeling and learning techniques to search for and decode nonlinear regularities in asset price movements. The author focuses on the case of IBM common stock daily returns. Having to deal with the salient features of economic data highlights the role to be played by statistical inference and requires modifications to standard learning techniques which may prove useful in other contexts

4. Designing a neural network for forecasting financial and economic time series

AUTHORS: Kaastra and M. Boyd

Artificial neural networks are universal and highly flexible function approximators first used in the fields of cognitive science and engineering. In recent years, neural network applications in finance for such tasks as pattern recognition, classification, and time series forecasting have dramatically increased. However, the large number of parameters that must be selected to develop a neural network forecasting model have meant that the design process still involves much trial and error. The objective of this paper is to provide a practical introductory guide in the design of a neural network for forecasting economic time series data. An eight-step procedure to design a neural network forecasting model is explained including a discussion of tradeoffs in parameter selection, some common pitfalls, and points of disagreement among practitioners.

To help frame your research clearly, we can divide the methodology into **Proposed Method** (your approach) and **Existing Methods** (previous or related approaches by others). Here's how you can structure both for your study on cryptocurrency price prediction using ANN and LSTM:

Existing Methods

1. **Statistical Models:**
   - **ARIMA (AutoRegressive Integrated Moving Average):** Frequently used for time series

   forecasting due to its simplicity, though it struggles with high volatility and nonlinear patterns in cryptocurrency prices.
   - **GARCH (Generalized Autoregressive Conditional Heteroskedasticity):** Effective for modeling financial time series with volatility clustering.

2. **Traditional Machine Learning Models:**
   - **Support Vector Machines (SVM):** Used for classification and regression tasks; limited in modeling sequential data.
   - **Random Forests:** Ensemble learning methods that can capture complex interactions but do not handle temporal sequences well.
3. **Basic Neural Networks:**
   - **Multilayer Perceptron (MLP):** A form of feedforward ANN that can model nonlinear relationships but lacks temporal awareness.
   - **Convolutional Neural Networks (CNN):** Recently applied to extract features from time series, though originally designed for image processing.
4. **Recurrent Neural Networks (RNN):**
   - **Standard RNNs:** Capable of handling sequential data but prone to vanishing gradient problems over long sequences.
   - **LSTM and GRU (Gated Recurrent Unit):** Designed to mitigate vanishing gradients and capture long-term dependencies effectively.

Proposed Method

In this study, we propose a comparative analysis of two deep learning frameworks:

1. **Artificial Neural Network (ANN):**
   - A fully connected feedforward neural network.
   - Trained on historical data including prices, volumes, and market indicators.
   - Relies on longer sequences of historical data to capture patterns.
2. **Long Short-Term Memory (LSTM) Network:**
   - A type of RNN specialized for learning sequential and temporal dependencies.
   - Able to capture short-term fluctuations more effectively.
   - Utilizes memory cells and gating mechanisms to retain relevant historical signals.

Key Components of the Method:

- **Dataset:** Historical price data of Bitcoin, Ethereum, and Ripple.
- **Input Features:** Price, trading volume, market cap, moving averages, RSI, etc.
- **Preprocessing:** Normalization of input features, data segmentation into training and testing sets.
- **Model Training:** Both ANN and LSTM are trained and evaluated using MSE and RMSE as performance metrics.
- **Comparison:** The predictive performance and memory efficiency of ANN vs. LSTM are compared.

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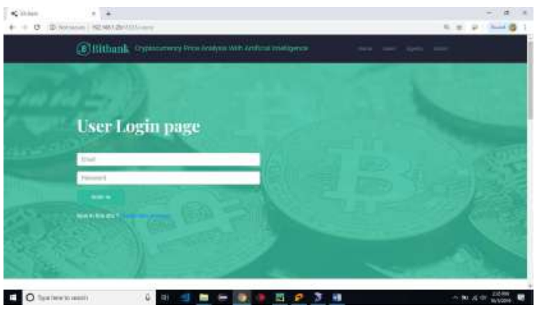
Sample Screens

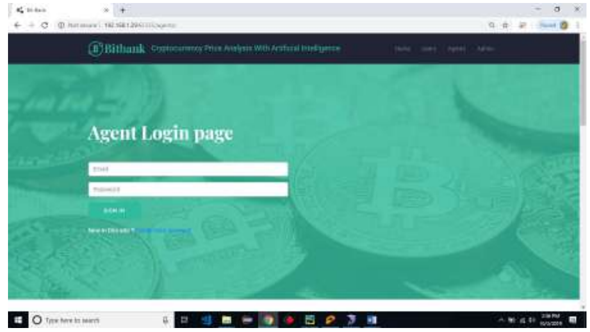
Home Page

Main Home Page

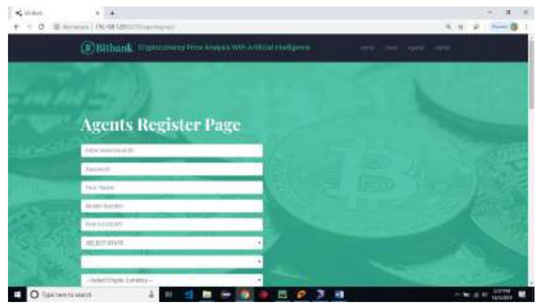


User Register Page

User Registration Form

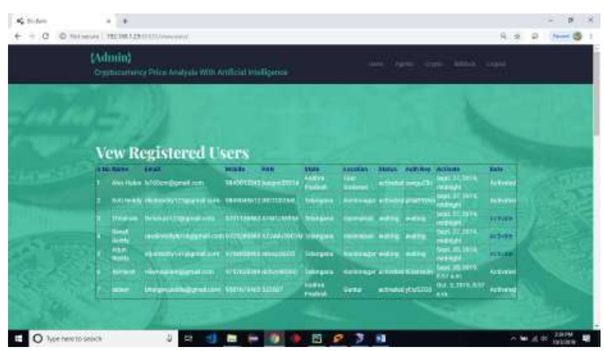


agent Login page



Agent Register page

Admin Login Page



Admin Activate Users

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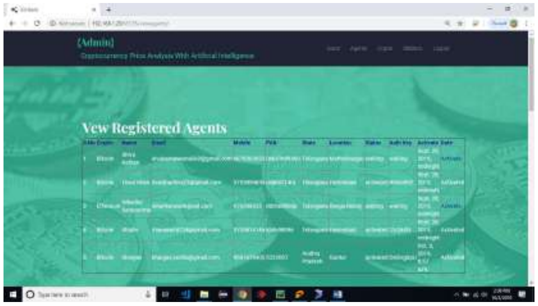
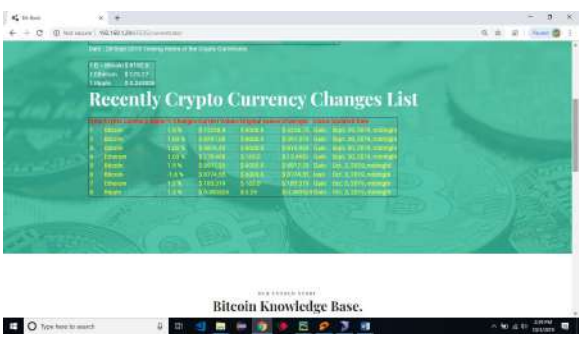
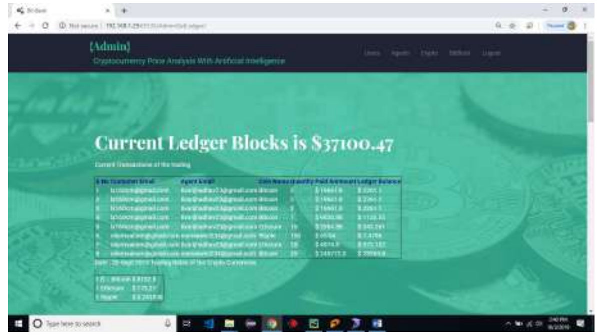


Admin Activate Agents

Current Price and Update



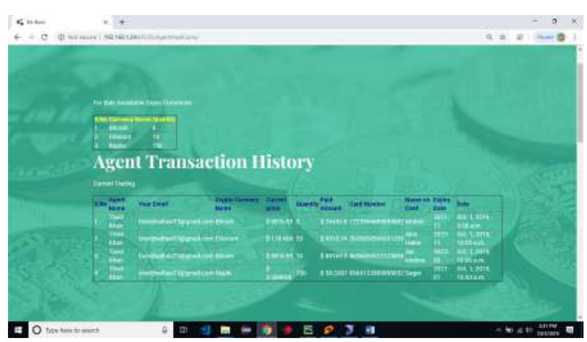
Crypto update history



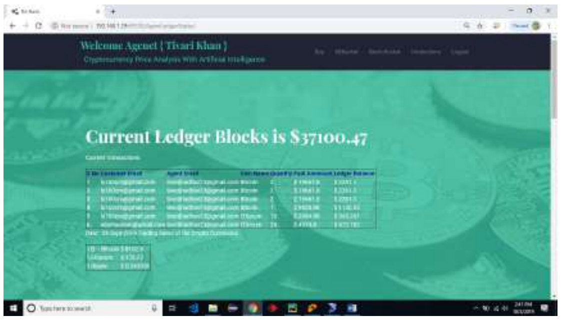
Blockchain ledger maintance

Agent buting crypto coins

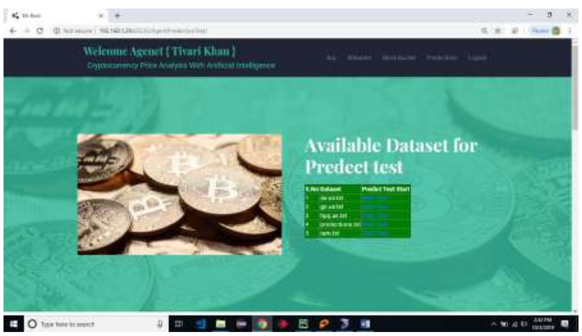
Agent buy Transactions



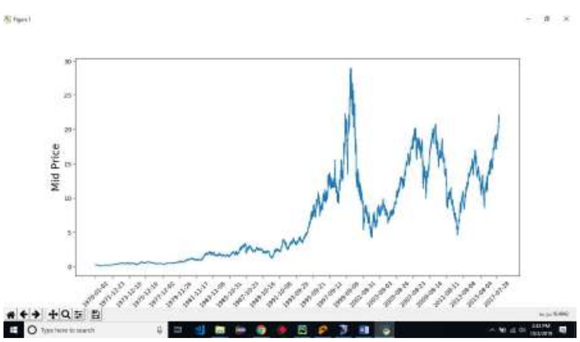
Agent transaction history



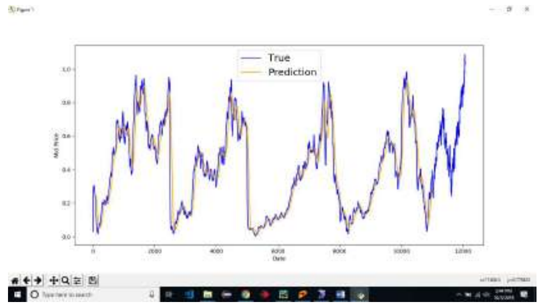
Agent view Ledger balance



Agent view predections dataset for test



Dataset analysis



True Predections

Predectins

User buying coins

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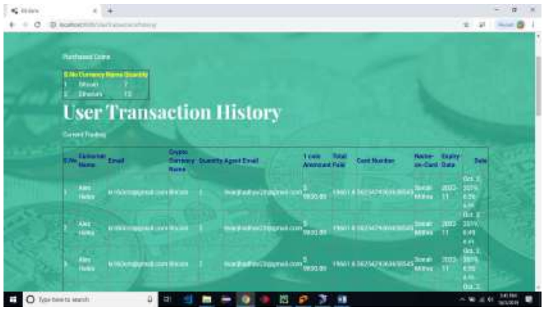
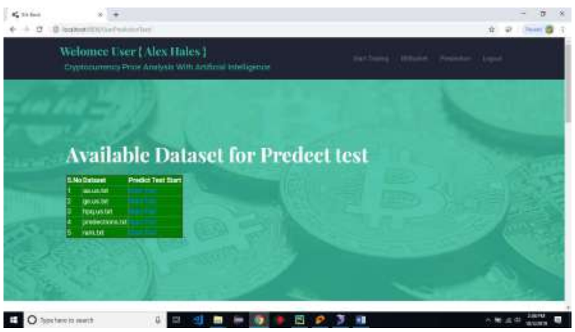


User purchased Coins



User can test the predections

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.

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