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Cryptocurrency Prediction Using Neural Network & Deep Learning

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Abstract— **Cryptocurrency is playing an increasingly important role in reshaping the financial system due to its growing popular appeal and merchant 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 influence 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 analyze the price dynamics of Bitcoin, Ethereum, 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 utilize 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 monitory and payment system that exist online via a controlled algorithm. When a miner cracks an algorithm 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 capitalization 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 decentralization 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

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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 exchange rate forecasting, for example, the monetary and portfolio balance models examined by Meese and Rogoff (1983, 1988) . Significant efforts have been made to analyze 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 hypothesize 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. LITERATURE SURVEY

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

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-network based feature engineering and machine learning optimization, we obtain up-down Bitcoin price movement classification accuracy of roughly 55%.

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

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

A. 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

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

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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.

III. IMPLEMENTATION

1. Data Collection:
Gather historical price data for Bitcoin, Ethereum, and Ripple from reliable sources such as cryptocurrency APIs or websites. Collect additional relevant data, including trading volumes, market capitalization, and any other features that might be useful for price analysis.

2. Data Preprocessing:
Clean the collected data by handling missing or inconsistent values. Normalize the data if required to ensure all features are on a similar scale. Split the dataset into training and testing subsets, ensuring a sufficient amount of data for each cryptocurrency.

3. Feature Engineering:
Analyze the collected data and identify features that may influence cryptocurrency prices. Extract and compute relevant features from the raw data. Consider using technical indicators, market sentiment data, or any other factors that might be informative.

4. Model Selection:
Choose two advanced artificial intelligence frameworks: Fully Connected Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) Recurrent Neural Network. ANN: A feedforward neural network that can learn complex patterns and relationships in the dataset: A type of recurrent neural network that can capture long-term dependencies and sequential patterns.

5. Model Training:
Train the ANN model using the preprocessed data. Experiment with different architectures, activation functions, and hyperparameters to achieve the best performance. Train the LSTM model using the same preprocessed data. Again, explore different architectures, activation functions, and hyperparameters to optimize performance. Split the training set further into training and validation subsets to tune the models' hyperparameters effectively.

6. Model Evaluation:
Evaluate the trained ANN and LSTM models using the testing set. Calculate relevant evaluation metrics such as mean squared error (MSE), root mean squared error (RMSE), or mean absolute error (MAE) to assess the models' accuracy. Compare the performance of ANN and LSTM models to understand their strengths and weaknesses.

7. Interpretation and Analysis:
Analyze the findings from the models' performance evaluation. Determine the factors that influence the value formation of Bitcoin, Ethereum, and Ripple, based on the models' predictions and insights. Compare the models' approaches: ANN relying more on long-term history and LSTM relying more on short-term dynamics.

8. Interpretation Validation:
Consider conducting statistical tests or further research to validate the models' interpretations and assess the robustness of the findings. Investigate the explanations provided by each model (ANN and LSTM) for the predictability of cryptocurrency prices.

9. Model Improvement:
Refine the ANN and LSTM models based on the analysis and interpretation results. Experiment with different model architectures, regularization techniques, or additional features to improve performance and interpretability.

V . RESULTS

5.1 HOME PAGE

5.2 USER REGISTRATION PAGE

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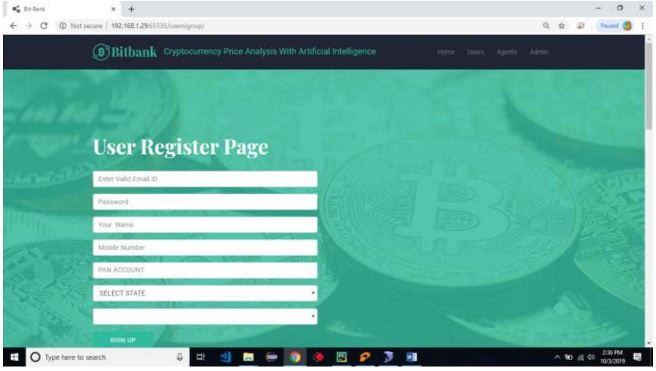
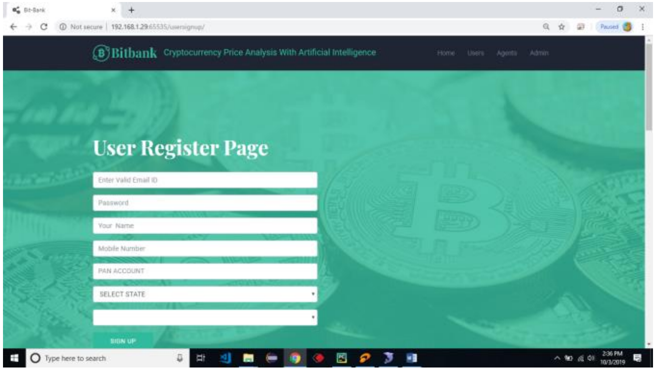
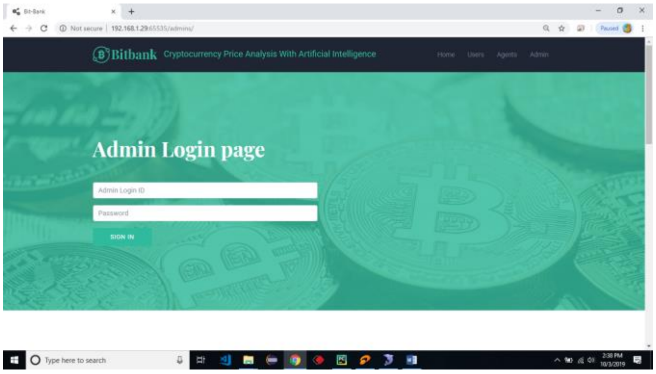


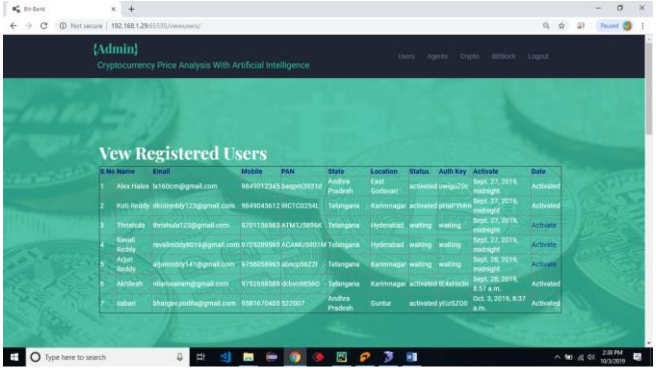
5.3 AGENT LOGIN PAGE



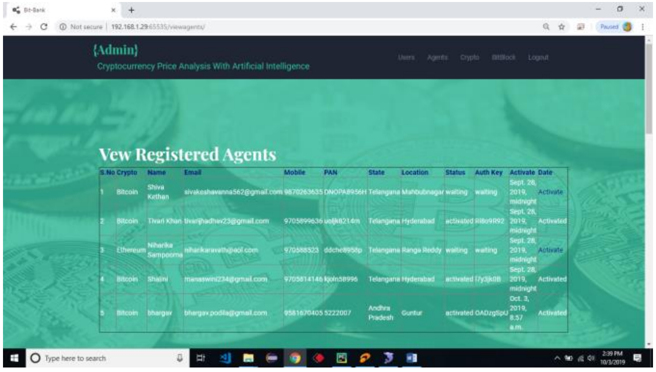
5.4 ADMIN LOGIN PAGE



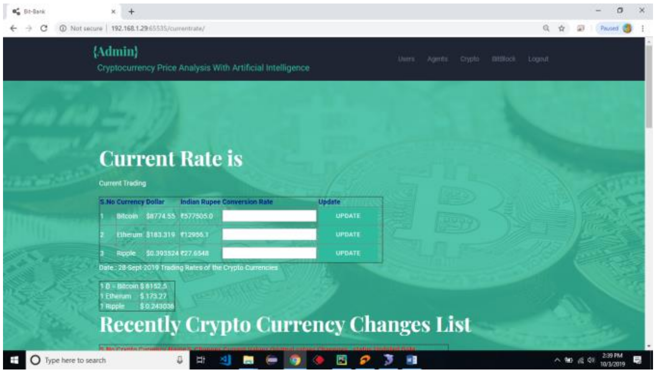
5.5 ADMIN ACTIVATE USERS



5.6 ADMIN ACTIVATE AGENTS



5.7 CURRENCY PRICE AND UPDATE



5.8 BLOCKCHAIN LEDGER MAINTAINCE

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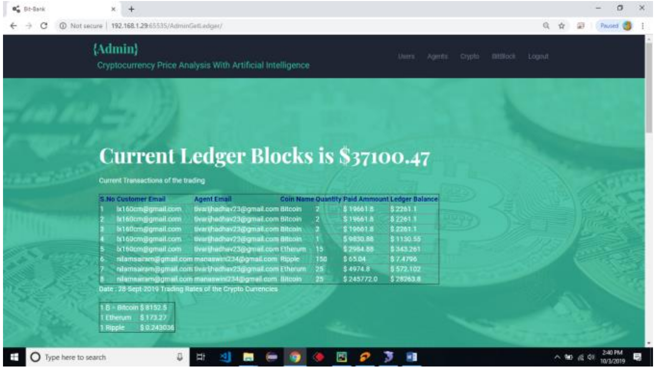
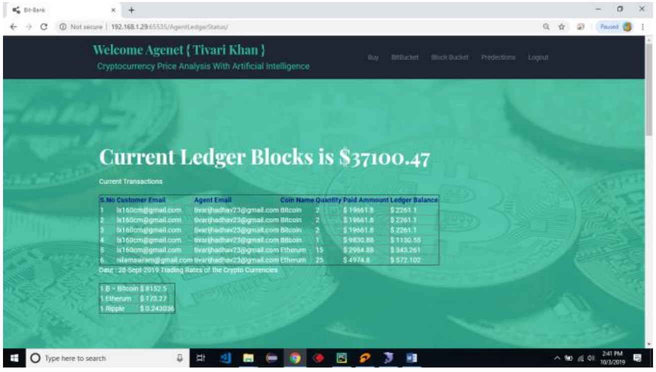
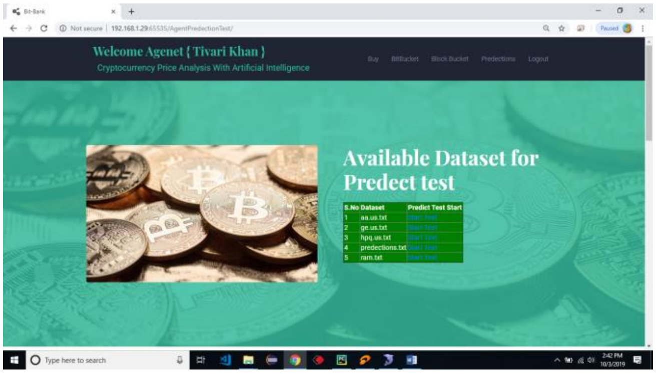


5.9 AGENT VIEW LEDGER BALANCE

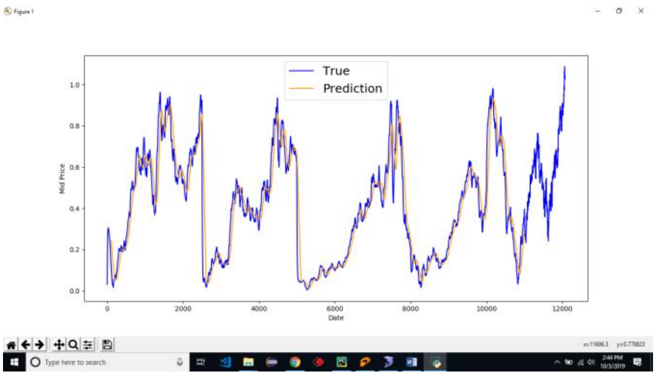


5.10 AGENT VIEW PREDICTIONS DATASET FOR TEST



5.12 DATASET ANALYSIS

5.13 TRUE PREDICTIONS



5.14 PREDICTIONS

IV. CONCLUSION

Cryptocurrency, such as Bitcoin, has established itself as the leading role of decentralization. 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 analyze and predict the price dynamics of Bitcoin, Ethereum, 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 analyze 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 utilize 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,

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