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# CRYPTOCURRENCY PRICE ANALYSIS WITH ARTIFICIAL INTELLIGENCE

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**Abstract:** Digital currency is assuming an undeniably significant job in reshaping the monetary framework because of its developing well known allure and shipper acknowledgment. While numerous individuals are making interests in Cryptocurrency, the dynamical highlights, vulnerability, the consistency of Cryptocurrency are still generally obscure, which drastically hazard the ventures. It is an issue to attempt to comprehend the components that impact esteem development. In this examination, we utilize progressed man-made reasoning structures of completely associated Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) Recurrent Neural Network to investigate the value elements of Bitcoin, Etherum, and Ripple. We find that ANN will in general depend more on long haul history while LSTM will in general depend more on momentary elements, which show the productivity of LSTM to use valuable data covered up in verifiable memory is more grounded than ANN. Be that as it may, given enough verifiable data ANN can accomplish comparative exactness, contrasted and LSTM. This investigation gives a one of a kind show that Cryptocurrency market cost is unsurprising. In any case, the clarification of the consistency could change contingent upon the idea of the elaborate AI model.

**Keywords:** ANN ; LSTM ; Cryptocurrency price prediction ; neural network

## 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 [1]. 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 [2]. 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) [3, 4], 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 [4]. In addition, the electronic payment system of Bitcoin is based on cryptographic proof rather than the trust between each other as

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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 [5]. Consequently, the rate of return of bitcoin investment for 2017 was over 880% [5], 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 [6, 7], 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 [5].

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 [1], 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 [8, 9]. Their models had also achieved great success. In [5], 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) [12]. Significant efforts have been made to analyse and predict the trends of traditional financial markets especially the stock market [10, 11], 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

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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.

## II. METHODOLOGY

**Data Collection & Data Analysis:** The historical prices data for cryptocurrencies were collected from https://www.blockchain.com/markets, and the total number of samples is 1030 trading days between 7 th August 2015 to 2nd June 2018. The price data comprised of four elements namely opening, high, low, closing prices. In this study, we analyse the price of three of the most popuer cryptocurrencies: Bitcoin, Ethereum and Ripple. We take the four elements as the input of our model, and then predict the next few days opening price which was used as the output of the model. We choose the opening price as the output for it reflects all the previous memories and events. The dataset was divided into training and testing sets according to an 80%, 20% ratio as this can avoid overfitting during de model training. The mean price of the three cryptocurrencies: Bitcoin $ 3082.084, Ethereum $ 194.810, Ripple $ 0.223, and the 95% confidence interval of their historical price: [2834.034, 3330.134], [176.977, 212.642], [0.196, 0.248]. As is shown in Figure 1, Bitcoin and Ethereum price have sharp fluctuations, and their standard deviations are as high as 4063, 292, 0.43 respectively.

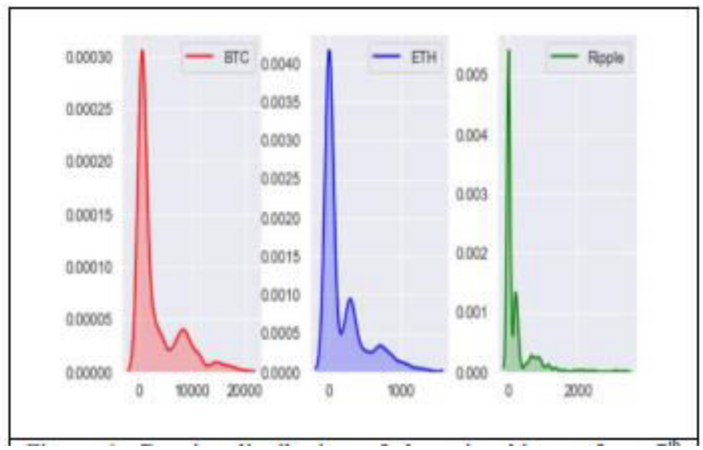


Figure 1: Density distribution of the price history from 7th August 2015 to 2nd June 2018, for Bitcoin (left panel), Ethereum (middle panel), and Ripple (right panel), respectively

Some works have been reported on the forecasting of financial markets using deep neural networks. In this study, we employ two prevailing deep learning models to analyze and predict crypto currencies price dynamics, including fully-connected Artificial Neural Network (ANN) and Long-Short-Term-Memory (LSTM) Recurrent Neural Network. For the LSTM, it includes three layers, each having ten nodes. Each LSTM cell state contains three gates: a forget gate, an input gate, and an output gate. LSTM controls the loss or addition of information through the gate to achieve the function of ignoring or memory. The forget gate is a Sigmoid function which has the input ht-1 and xt where the former is the output of the last

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unit, and the latter is the input of this unit. The Sigmoid function can produce ft which is a value in [0,1] for each item in Ct-1 (internal state), '0' means that 'keep this completely' and '1' represents 'forget this completely', to control the extent of forgetting of the last unit.

The ANN model used in this study is a fully-connected multi-layer perceptron that imitates the structure and function of the human brain, and it has a strong ability of in approximating non-linear data. In this experiment, our ANN model has three components: the input layer, hidden layer, and output layer. Each layer has ten nodes. The input layer gives a weight wij to the input, and there is an activation function-Sigmoid function f. Then xi he output of the hidden layer will be passed to the output layer which is the same as the last process, and then we can get the final output. We use the historical data to predict the trend of the cryptocurrency market, but what can the historical memory length that we use produce the most relevant results? With the same length of historical memory, will the different range of memory that we want to predict influence the accuracy of the model? We analyse the most appropriate internal memory and predictive memory length in understanding the cryptocurrency price dynamics. We try five different internal memory lengths: 7, 14, 21, 30, 60 days, and then combine with five predictive memory lengths: 1, 3, 5, 7, 14 days.

## RESULTS AND DISCUSSION

ANN Estimate of time Series Memory For the first part of ANN model, we use an ANN model to predict the price of Bitcoin one day into the future using five different lengths of memory: 7, 14, 21, 30 and 60 days. To measure the error between the data and model, we use the mean square error and the correlation. The results of our modeling experiments are shown in Fig. 2. It shows that the price of crypto currencies exhibits a long-term self-explain feature. By learning the full history of the previous month, the ANN model prediction of Ethereal is largely improved, compared with those short-term cases (blue bars in Fig. 2). Furthermore, concerning Bitcoin and Ripple, an even longer history of price (60 days, green and orange bars in Figure 2) is beneficial. However, we also find that solely increase the length of historical data as input features not necessarily induce a better model, the model performance is offset by introducing more model parameters (as increase of input features). For example, for Ethereal, using 60-day price history as input features performs worse than using 30-day price history. Nevertheless, all ANN models generally capture the variation of the price dynamics, indicated by the high correlation between observed and modeled crypto currencies prices.

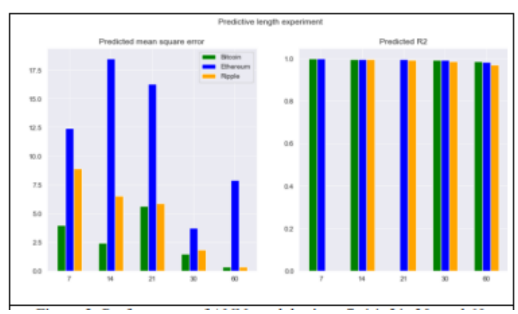


Figure 2: Performance of ANN model, given 7, 14, 21, 30, and 60 days price history as input features. Left and right panels represent model-data mean square error and Pearson correlation.

For the second part of ANN experiment, we need to figure out the most efficient predictive length (1, 3, 5, 7, 14 days) of cryptocurrencies

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prices given a 30-day historical memory. As shown in figure 3, for the Bitcoin and Ripple, one day price in the future can be predicted relatively well, and we also observed that the prices in three days of Ethereum could be forecasted more accurate than its other prices in the future.

## 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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