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Cryptocurrency Price Investigation using fully connected artificial neural network and long short-term memory

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Abstract: *Cryptocurrency becoming more popular and, although held by traders, are increasingly playing an important role in reshaping the financial system. While many people are investing in cryptocurrencies, the essential characteristics, reliability, and predictability of cryptocurrencies are largely unknown, dramatically increasing investment risk. It is a commercial company that seeks to eliminate attorneys who influence cost structure. Here we look at the very relevant state-of-the-art artificial intelligence frameworks of artificial neural network (ANN) and long short-term memory (LSTM) to investigate the rate dynamics of Bitcoin, Ethereum and Ripple. We found that ANN computes more in long-term history, while LSTM computes more in short-term dynamics, indicating that LSTM is more effective than ANN in exploiting useful information hidden in verbal memory. Still, with enough old information, ANN can achieve the same accuracy as LSTM. This dream provides a unique demonstration that the market value of cryptocurrencies is predictable. Still, predictive clarity should fluctuate depending on the complexity of the specific device study model.*

Keywords: *Artificial neural network, long short-term memory, Cryptocurrency.*

I. INTRODUCTION

Cryptocurrency is a peer-to-peer virtual money and charging device that exists online through a structured algorithm. When a miner cracks an algorithm to document a block of transactions on a public ledger called a blockchain, cryptocurrency is created as the block enters the blockchain. It allows people to save and convert via encryption protocol and distributed network. Mining is an important and competitive element of the cryptocurrency system. A miner with more computing power has a better chance of finding as many new coins as possible. Bitcoin is one of the most important and well-known digital currencies (its market capitalization was over US$7 billion in 2014, and then increased dramatically to US$29 billion in 2017), first coined in 2008 by Satoshi Nakamoto. was introduced. Bitcoin, most strikingly, is decentralized, able to eliminate the

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implications of repeating all proofs of work throughout the blockchain, playing an important role as a perceived middleman and, indeed, its Can be used extensively, such as logging. Charitable support to avoid corruption. Additionally, Bitcoin incorporates a controllable anonymity scheme, and it improves the security and anonymity of users by using this era. For example, we could leverage these blockchain devices to create ID cards, and no longer do. We can only protect your privacy but verify your identity. Nowadays, investing in cryptocurrencies, such as Bitcoin, is one of the most effective ways to become profitable. For example, the price of Bitcoin rose rapidly in 2017, from a significant low point of $963 on January 1, 2017, to a high of $19,186 on December 17, 2017, and closing at $9,475 at the end of the year. As a result, Bitcoin investment recovery rate for 2017 exceeded 880%, which is an impressive and sudden perspective for most traders. Predicting the price of cryptocurrencies can help us become smarter investors. Although market forecasting is effective for traditional financial sectors and financial governance due to its blockchain network functions. Furthermore, with digital payment investments in cryptocurrencies, ordinary people of investors cannot earn such income as they are insignificant to the main factors affecting the dynamics of cryptocurrencies and the trends of bitcoins. Therefore, increasing human awareness of the key elements of the Bitcoin device is based entirely on cryptographic evidence and not trust between dynamics, troubled by its complex nature, which is somewhat predictable and comprehensible. For example, when Bitcoin is in short supply, its value can be inflated with the help of its dealers as buyers who see Bitcoin as a profitable option A financing prospect may have a strong preference for paying bitcoins. Additionally, the price of Bitcoin can be easily influenced by some influential external factors including political factors. Although current efforts in cryptocurrency analysis and forecasting are limited, some research aims to understand cryptocurrency time series and build statistical models to reproduce and predict price dynamics. For example, Madan et al. It accumulated the value of bitcoins with time intervals of 0.5, 1 and 2 hours, and combined it with the blockchain network, the underlying generation of bitcoin. Its predictive version leverages random forests and binomial logistic regression classification and the model's accuracy in predicting the price of Bitcoin is approximately fifty-five percent. Shaw et al. Used Bayesian regression and leveraged Bitcoin's high-frequency (10-

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second) spending statistics to improve Bitcoin investment outlook. His models also achieved surprising success. In a multi-layer perceptron (MLP)-based forecasting model was provided to predict tomorrow's bitcoin price using two sets of inputs: main type of input: open, low, Higher and closer rates, and another set of entries. : Moving averages of short (five, 10, 20 days) and long (one hundred, two hundred days) windows. During verification, their model was shown to be ninety-five percent accurate.

We intend to use an artificial intelligence modelling framework to determine the rate dynamics of the most popular cryptocurrencies. Here we use an artificial intelligence corpus, long-short-term memory, to analyse and predict the price dynamics of Bitcoin, Ethereum, Ripple and many similar cryptocurrencies. Long short-term memory (LSTM) to allow us to develop a predictive model to predict the costs of all cryptocurrencies. Additionally, we will be reducing noise in the datasets for greater model effectiveness and precision.

II. LITERATURE SURVEY

In [1] Neural Networks for Economic Forecasting. The IBM Daily Inventory Response Report case is provided with some Halbert White results. A collection of authors on neural network modeling and domain techniques is presented. A list of some of the results of deliberate design is formulated using neural network domain and modeling techniques to detect and decode nonlinear anomalies in asset rate movements. The author focuses on the case of IBM's daily normal inventory returns. Addressing the salient features of valuable information highlights the role that statistical inference must play and requires variations on traditional learning techniques that may be feasible in specific environments.

[2] In Cryptocurrency Value Formation, a Case Study That Developed a Pay-Per-Product Model to Appreciate Bitcoin Adam, Hayes. It then attempts to identify the potential value proposition(s) that cryptocurrencies exist in the market using cross-sectional empirical records that examine the 66 most exploited analog currencies. A regression model is projected that points to the three main drivers of cryptocurrencies that are experiencing a coin 'mining' problem. unit product rate; And the cryptographic algorithm is secure. It is equal to the relative difference in the value of one coin to the value of another coin in the frame, keeping them all equal. Bitcoin used pegged relative rates, which avoided much of the rate volatility associated with the dollar exchange rate.

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Effective regression models can be used to better understand the relative value drivers observed within the mainstream cryptocurrency space. A commodity value model is recommended for determining bitcoin prices, using the view below, with energy as the main input. This theoretical version provides the balancing factors for starting and stopping the product and the bitcoin exchange rate in the macro function, producing beneficial results for the user with the role. The Bitcoin commodity appears to operate as a competitive commodity demand. In this case, miners will produce until the price of their body is equal to the production of their body.

In [3] Bitcoin transaction forecasting authors, Alex Graves, Benjamin O. Bitcoin, the world's most popular cryptocurrency, allows users to trade easily and discreetly over the Internet. Consumers, companies, traders and speculators have recently been interested in the Bitcoin environment. While much research has been done to analyze the architecture of the Bitcoin network, less has been done to look at how the network affects the price of Bitcoin as a whole. In this study, we analyze the ability of blockchain network-based features to predict Bitcoin price changes. Using system learning optimization and feature engineering based entirely on blockchain networks, we achieve an accuracy of approximately fifty-five percent above and below classification of Bitcoin prices.

[4] Bitcoin to US Dollar Exchange Price Prediction Using Synthetic Neural Community Techniques, authors Arief Radityo, Qorib Munajat and Indra Budi, cryptocurrency exchange is currently a popular form of financing. The cryptocurrency market has functioned similarly to the forex and stock markets. However, due to its volatility, cryptocurrency exchanges lack a predictive tool for investors to help them make investment decisions. Nowadays, artificial neural network (ANN) computing tools are commonly used in inventory forecasting and foreign exchange markets.

Cryptocurrency is undoubtedly one of the most innovative and volatile investment styles. Fortunately, thanks to the growing evolution towards cryptocurrencies, companies are now willing to expand their portfolios in a decentralized manner and new investors are emerging. Moreover, people will use not only computers but also different types of portable devices, such as smartphones and tablets, to browse websites and various packages as a result of shopping, as the music era is advancing these days. The developed device allows to predict the cryptocurrency rate. To predict this rate, knowledge acquisition and statistical processing machines are hired. LSTM, RNN, call tree, ANN, and rectangular regression measures should enable the training of Bitcoin expenses as efficiently as statistical statistics. It is possible to wait for a cryptocurrency address on this device for multiple time intervals. The time required for model compilation and its prediction accuracy is quite insignificant for different algorithms. Although current efforts in the quadratic level of cryptocurrency value forecasting and analysis are limited, many studies are on the way to understanding cryptocurrency statistics and building mathematical models applied to reconstruct and anticipate value dynamics.

III. METHODOLOGY

ARTIFICIAL NEURAL NETWORK (ANN)

Biological neural networks serve as the basis for the form and function of ANN architecture. ANNs are also made up of neurons, which can be organized into multiple layers, similar to neurons in the brain. A typical neural network called a "Feedback Neural Network" has 3 layers: an output layer that provides the answer to the problem, an output layer that receives external data for pattern recognition. , and a hidden layer that acts as an intermediate layer between the 2. Through acyclic arcs, adjacent neurons within the input layer and output layer are connected. ANN uses a training algorithm to investigate data sets and update the neuron's weights based on the error rate between the target and actual output. For the most part, an ANN uses a back-propagation approach as a set of learning rules to familiarize itself with a data set. ANNs are artificial neural networks that acquire deep knowledge of strategies. ANN was developed as a way to simulate how the human brain works. Biological neural networks and artificial neural networks work in remarkably similar ways, albeit with some variations. Only numerical and structural facts are perpetuated by the ANN algorithm. The input layer, the hidden layer (or layers), and the output layer make up the structure of the network. Because of their multiple layers, they are commonly known as MLP (Multilayer Perceptron). A hidden layer can be thought of as a "detail layer", which takes some large patterns from the inputs and passes them directly to the next layer for further evaluation.

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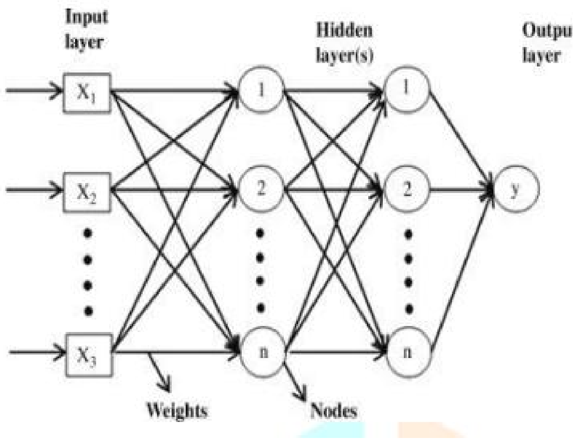

Fig.1 ANN Architecture

LONG SHORT-TERM MEMORY (LSTM)

Information can be retained thanks to a deep learning sequential neural network called a short-term memory network. It is a specific type of recurrent neural network that can solve the vanishing gradient problem faced by RNNs. Hochreiter and Schmidhuber built LSTM to solve the problem with traditional rnn and machine learning techniques. Python's Keras package can be used to implement LSTM. Due to vanishing gradients, RNNs have the drawback of not being able to remember long-term dependencies. Long-term dependence problems are specifically avoided when designing LSTMs. In the previous section, we found that long-term memory solves the vanishing gradient problem of RNNs. In this section, we'll explore how it does this by understanding the architectural design of the LSTM. LSTM works like an RNN cell at a high level. The inner workings of an LSTM network are seen below. As seen in the figure below, the LSTM network design is composed of three sections, each of which serves a distinct purpose.

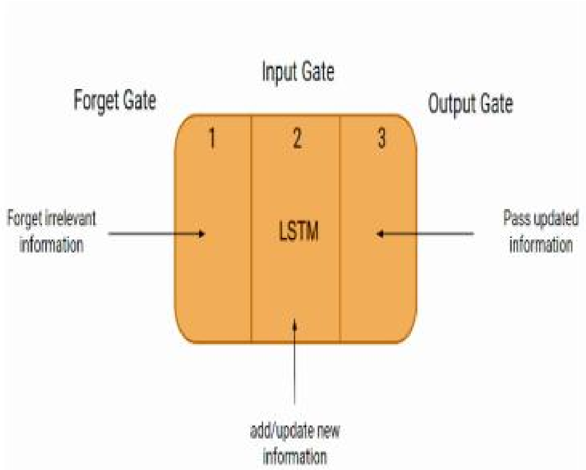

Fig.2 LSTM architecture

Data Collection & Data Analysis

Historical cryptocurrency fee records were collected from https://www.Blockchain.Com/markets, and the total number of samples is 1030 trading days between August 2015 and June 2, 2018. Data charges mainly consist of 7 out of 4 elements. Opening, high, low, final costs. In this article we analyze the price of three of the most popular cryptocurrencies: Bitcoin, Ethereum and Ripple. We take the four factors as input into our model and then expect the model to produce a consumption rate within the next few days. We chose the whole charge because its result reflects all previous

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memories and events. The data set is divided into training and test set in the ratio of 80% to 20%, as this version can avoid overfitting during training. Implied value of three cryptocurrencies: Bitcoin $3082.084, Ethereum $194.810, Ripple $0.223, and c programming language with 95% confidence of its historical value: [2834.034, 3330.134], 712.69, 712, 760 0.248]. As shown in Figure 1, the loads of Bitcoin and Ethereum have large fluctuations and their standard deviation reaches 4063, 292, zero. Forty-three respectively.

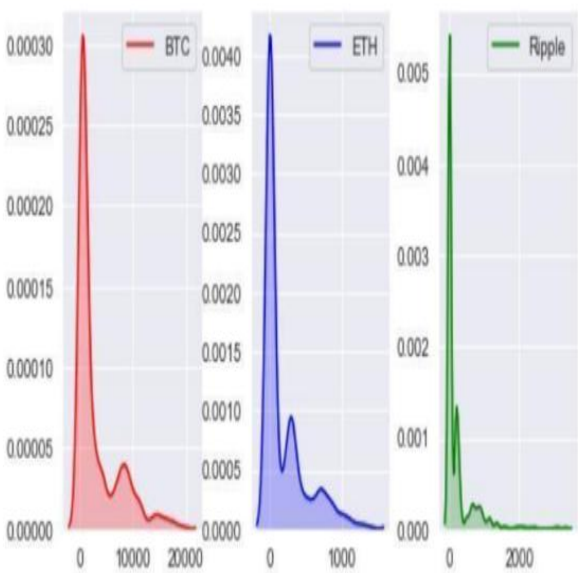

Fig.1 Figure 1.Density distribution of the price history from 7th August 2015 to 2nd June 2018, for Bitcoin (left panel), Ethereum (middle panel), and Ripple (right panel), respectively

Models

Some work on forecasting financial markets using deep neural networks was presented. In this view, we employ achievers who have deep knowledge of models to test and anticipate the charging dynamics of cryptocurrencies, including fully connected artificial neural networks (ANN) and long and short memory recurrent neural network term (LSTM). For LSTM, it consists of three layers, each with ten nodes. Each LSTM cell state includes three gates: a forget gate, an input gate, and an output gate. LSTM controls the loss or gain of data through a gate to achieve the neglect or memory characteristic. The bypass gate is a sigmoid characteristic with inputs ht1 and xt where the first is the output of the rest unit and the second is the input of that unit. The sigmoid feature can generate a foot with value in [0,1] for each object in Ct-1 (internal state), '0' meaning 'keep it completely' and '1' meaning ' Ignore it completely', the degree to which the last unit to be manipulated is forgotten.

$$ft = sigma(Wf.[ht1, xt] + bf) \quad (1)$$

An intergate generates this by sigmoid activation, and the tanh characteristic that generates the potential internal country (). Both of these control how much new data will be introduced into Ct-1 to change the actual input state to Ct:

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it = sigma(Wf.[ht-1,xt]+bf) (2)

$$\vec{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right)$$

$$C_t = f_t * C_{t-1} + i_t * \vec{C}_t$$

IV. CONCLUSION

Cryptocurrency such as Bitcoin, have established themselves as decentralization leaders. After Bitcoin, many other cryptocurrencies emerged, including Ethereum and Ripple. Many people hold them as a form of speculation due to the extreme unpredictability of their value. As a result, it is very important to understand the basic characteristics and predictability of different cryptocurrencies. In this study, we analyse and predict bitcoin price movements using two unique artificial intelligence frameworks: fully connected artificial neural network (ANN) and long short-term memory (LSTM). We show that despite the differences in the underlying structure, the ANN and LSTM models are similar and perform quite well in price forecasting. The effects of historical memory on model predictions are then further investigated. We found that ANN relies more on long-term history, while LSTM relies more on short-term dynamics, indicating that LSTM is more effective than ANN in exploiting relevant information hidden in historical memory. This study is one of its kind and shows that the market value of cryptocurrency is predictable. However, depending on the nature of the underlying machine learning model, prediction accuracy may vary.

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