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A Self-Adaptive Deep Learning-Based Algorithm for Predictive Analysis of Bitcoin Price

Nishant Jagannath[1], (Member, IEEE), Tudor Barbulescu[1], Karam Sallam[2],(Member, IEEE) , Ibrahim Elgendi[1], (Member, IEEE), Asuquo A. Okon[1] (Member, IEEE), Braden McGrath[3], Abbas Jamalipour[4], (Fellow, IEEE), Kumudu Munasinghe[1], (Senior Member, IEEE)

[1]School of IT and Systems, University of Canberra, ACT 2601, Australia
[2]Faculty of Computers and Informatics, Zagazig University, Egypt
[3]Faculty of Human Factors and Behavioral Neurobiology, Embry-Riddle Aeronautical University, United States of America
[4]School of Electrical and Information Engineering, University of Sydney, NSW 2006, Australia

Corresponding author:Nishant Jagannath (e-mail: nishant.jagannath@canberra.edu.au).

ABSTRACT Bitcoin generates a massive amount of data every day due to its innate transparency and capacity of operating completely decentralised. In this paper, we introduce on-chain metrics derived from data on the bitcoin network that enable us to describe the state and usage of the underlying network. Based on their characteristics, we classify them into user, miner, exchange activities and run a correlation analysis with the price to understand the dynamics of bitcoin's price and its underlying mechanics. Using the correlated data, we develop a deep learning model. However, determining the best values of parameters in a deep learning model can be a very challenging and time-consuming task. Hence, we propose a self-adaptive technique using a jSO optimization algorithm to find the best values of these parameters to accurately predict the price of bitcoin. Compared to traditional LSTM model, our approach is highly accurate and optimised with a minimum error rate.

INDEX TERMS Bitcoin, Blockchain, Deep neural network, Differential evolution, Evolutionary algorithms, jSO, LSTM

I. INTRODUCTION

Blockchain is a distributed ledger technology, similar in structure to a linked list copied across thousands of computers, with technology in place that ensures that each computer holds a copy of the same object. The transactions are stored in blocks - the original block being called the genesis block and each subsequent block added to the network contains the hash, timestamp and transaction data of the previous block. The new block is stored, distributed to the blockchain network and maintained by peers in the system. Apart from its use in cryptocurrency, blockchain technology is also used in a variety of applications like electronic healthcare and identity management systems [1].

Blockchain technology and its most famous application to date - Bitcoin, were introduced to the world through a paper written under the pseudonym of Satoshi Nakamoto in 2008 [2]. The fundamental reason for Bitcoin's success is that it emerged as the first digital currency which solved the double spending problem, enabling a new way of transmitting value online in a pure peer-to-peer fashion, without the reliance on a trusted third-party. Besides giving birth to a secure and inexpensive way of transferring value through a decentralized, peer to peer network, bitcoin also gave birth to what is arguably becoming a new asset class through the rise of other cryptocurrencies.

A. BIRTH OF A NEW ASSET CLASS

Bitcoin (BTC) is the first decentralised cryptocurrency; its genesis block being minted in 2009. However, since 2011, a plethora of other cryptocurrencies known as altcoins - were created and are still in use today. Initially, altcoins were only forks of bitcoin, meaning that they started from the same code-base (hence the name - alternative coin). These altcoins lowered the entry barrier to crypto market thus attracting a lot of players including scammers, malicious players and low quality projects. However it also created room for more serious projects to come on board -the most successful one being Litecoin, which is currently the fifth-largest cryptocurrency in terms of market value [3].

Nowadays not all cryptocurrencies are altcoins - not all are forked versions of bitcoin. There are a lot of other projects that started with an original code - such as Ethereum - a blockchain platform that not only allows for the transfer of value in a decentralized way, but which also enables participants to create and participate in rule-based smart contracts (pieces of code) that run on decentralised infrastructure similar to that of bitcoin; or by forking other cryptocurrencies, such as Monero (which was a fork of Bytecoin - another cryptocurrency with an original code-base). However, there still exist a lot of other altcoins that originated from bitcoin currently active, that have been operating for years under different codebases to that of bitcoin.

Cryptocurrencies were at first used as a highly speculative and relatively long-term investment; originally, the only way to get some bitcoin was through mining, which is the process through which the network is secured and bitcoin is released in to circulation. Agents who participate in the process of securing the network are called miners and are rewarded with bitcoin for putting their computational hardware to the network's use. These were early days (pre 2010) when there were no vendors or exchanges with bitcoin only being used by a small group of people. Around mid-2010 the first bitcoin exchange was launched - BitcoinMarket.com through which people could buy BTC in exchange for USD.

With mentions in the mainstream media of reaching US dollar parity in 2011, the popularity of Bitcoin started to rise and a few altcoins came into existence. First one was Namecoin, initially announced in April 2011, followed shortly after with the launch of Litecoin in October 2011. The altcoin boom didn't start until the end of 2013, when new coin were launched almost every week. This acted as the birth of a larger, highly speculative [4] trading market - where traders buy and sell different pairs of cryptocurrencies based on technical indicators and fundamental analysis. It has been shown that these traders exhibit similar behaviour to that of traders in the forex and the stock markets [5].

Technical, Fundamental and Quantitative analyses are the most popular methods used to analyse a crypto asset. These methods are used as directional thesis for crypto investment, with technical analysis being the most dominant choice. Although the reports describe that profits over the years have declined using technical analysis, studies suggest that there is a substantial increase in terms of profitability in foreign exchange markets [6], in addition to this, investors still focus on technical indicators as a part of their investment strategies. In recent years, technical analysis has gained immense popularity in crypto trading as it focuses on profits using statistics and volume of the data. The challenge with technical analysis is when it is used with cryptocurrency market, the indicators in crypto change rapidly leading to reduced efficiency in predicting the pricing of a crypto asset, to combat these challenges researchers have focused on Technical indicators with machine learning algorithms to predict the price of crypto assets, primarily Bitcoin [7].

As bitcoin is a permission-less public blockchain, researchers focused on statistical properties of bitcoin prices using blockchain information primarily core network activities like hash rate, transactions and block height and their correlation with bitcoin price [8] while other studies focused on identifying the relationship between Bitcoin price, Google and Wikipedia [9].

While some studies have considered blockchain information such as network activities to predict the price, most of the previous studies have focused on modelling and predicting bitcoin price using machine learning algorithms, it presents many overlooked opportunities to realize the value and information of bitcoin. Since blockchain is the underlying technology of bitcoin, the influence of core components of bitcoin including miners, nodes and exchanges on the bitcoin price are understudied. In this paper, we investigate the activities related to the users, exchanges and miners on the bitcoin network and to better understand the dynamics of bitcoin and aim to give a comprehensive overview of the linear influence of on-chain activities on the price of bitcoin.

The rest of this paper is structured as follows. In Section II, a literature review of related work is presented highlighting current research on the predictive analysis of bitcoin prices. Section III describes the proposed design and methodology employed for this research including data collection, data characteristics, and analysis metrics and approach. Section IV deals with data analysis, where on-chain activities are categorized and correlated with the price of bitcoin in order to gain a deeper understanding of the dynamics of bitcoin prices while Section V introduces the jSO-based optimization model, describes the jSO algorithm as well as provide justification for its adoption. A brief description of the experimental setup is provided in Section VI while the results of this work and the analysis of these results are presented in Section VII. Finally, in Section VIII, we summarize our research, drawing conclusions from the results and giving directions for future work.

II. RELATED WORK

Technical Analysis has a long and rich history in academic literature. For example, Kamrat et al. focuses on technical analysis for crypto trading, specifically on Turtle Trading System, upon modification yields more profitability than the original Turtle trading system which indicates buy or sell signals for a stock during breakouts that is generally defined by a set of rules. [10]. Many studies have also focused on using various machine learning approaches for improving prediction rate for bitcoin prices [7] [11]. A study by Shynkevich points out that with the advent of regulated derivatives exchanges for trading bitcoin futures, the ability of technical analysis to predict bitcoin prices have declined, indicating a significant increase in market efficiency in bitcoin prices [12]. Recent study also suggest that traditional economic theories are insufficient in predicting the volatility associated with the price of bitcoin [9].

Since bitcoin uses open data architecture, blockchain analytics can indicate patterns of user behaviour and other activities. However, the drawback with data on public blockchain is that the size of blockchain data is massive and has exponentially increased over time with approximately 300GB in 2020. Parsing this huge amount of data becomes cumbersome and inefficient. However, a recent study developed a open source framework to acquire the data available on the blockchain in real-time [13]. Using the API of these frameworks, a recent study designed an open data architecture to analyse the massive amount of blockchain data efficiently using high-fidelity graphs [14] [15]. As blockchain is primarily driven by user activities, analysis of the user transactions on the blockchain network using A.I has become a key factor in indicating patterns for fraud detection in the network [16].

Recently, researchers have utilized the features of the bitcoin network to understand the dynamics of the bitcoin and concluded that the hash rate, difficulty and transaction cost are highly correlated with price [17]. Further, using this correlation, a machine learning approach was used to achieve a better accuracy rate for predicting bitcoin prices [18]. An empirical study by Jang et al. explains the high volatility of the bitcoin price using the core network features of blockchain information and macroeconomic factors like global currencies and exchange rates between major fiat currencies [8]. As bitcoin is a decentralised cryptocurrency, this implies that peer-to-peer consent is required for its operation, thus the data related to core network activity are stored natively on blockchain. This suggests that on-chain metrics could prove to be one of the best means of obtaining very useful information available on the bitcoin network. In this paper, we take a comprehensive approach to the blockchain information using the on-chain metrics to combine a profusion of datasets that represent activities related to users, miners and exchanges. We correlate the on-chain data with price of bitcoin to apply the knowledge to deep learning models for predicting the future behaviour and important price movements in the bitcoin market.

III. PROPOSED DESIGN AND METHODOLOGY

Most of the previous studies have focused on modelling and predicting Bitcoin price by identifying its linear relationship to macroeconomic factors like crude oil, exchange rates between global currencies [8], without realising the value and information of the core activities available on-chain. In this section, we outline the methodology used to categorise the on-chain metrics based on the characteristics of data collected and we outline the analysis metrics and approach used on our dataset to develop a prediction model for bitcoin.

A. DATA COLLECTION

For this study, we acquired data from public blockchain of bitcoin and API of online resources from 2016 to 2020 [19] [20] [21]. Using the on-chain data from these resources, we categorise and analyse metrics from each category against the bitcoin's price. Although researchers in the previous work have considered external variables such as crude oil, government policies and other fiat currencies [8] to understand the volatility in bitcoin's price, in this study, we primarily focus on providing a comprehensive overview by including on-chain metrics related to miners, users and exchange activities that potentially impact the bitcoin prices. Some of the on-chain metrics acquired include block count, transaction volume, transaction count, hash rate, difficulty, block height, miners balance, miners revenue, miners inflow, miners outflow, miners to exchanges, exchange balance, exchange inflow, outflow, NetFlow, daily active addresses, total addresses, UTXO and wallets address > 1, >10, >100.

B. DATA CHARACTERISTICS

In 2017 many exchanges and key industry players adopted Segregated Witness (SegWit) protocol [22] – an efficient way to scale data on bitcoin by freeing up additional space in the headers of the block - to accommodate a greater number of transactions in a block. Since its adoption the size of the block has steadily increased from 1 MB in 2017 to 1.3 MB in 2020. The computation time in bitcoin network is calculated using the time interval between each block and the difficulty level. The hash rate is calculated in a way that the computation time is always set to an average of 10 minutes to maintain high level of security and resistance to attacks on the network.

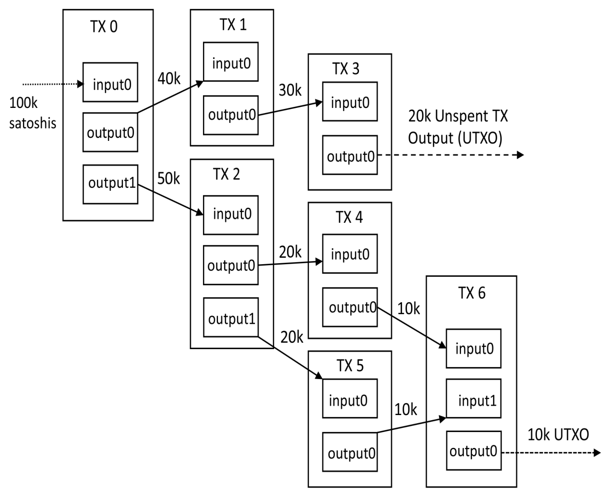

FIGURE 1. Triple-Entry Bookkeeping (Transaction-To-Transaction Payments).

In blockchain, a block also contains an answer to a unique, difficult-to-solve mathematical puzzle; before the block was put into circulation, all the information within that block (besides the answer to the puzzle) was collected by all the miners. The first miner to solve the puzzle derived from that information receives what is called a block reward. Block rewards started at 50 Bitcoins and halved every 210,000 blocks, or approximately 4 years. The difficulty of the network is

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given by this puzzle - which is reset every 2016 blocks (or about 2 weeks) such that the network can mint a block every ten minutes on an average.

Since 2011 the number of unique addresses has seen an unprecedented growth in bitcoin with increase in price. The number of active addresses in the network is proportional to the number of transactions sent and received on the network successfully. Bitcoin also employs the unspent transaction output (UTXO) record-keeping model, which presents valuable information through which the age of each coin in circulation can be inferred. This feature is however not available for Ethereum which is based on the Account/Balance model. It is interesting to note that even though the latter model does not register the age of a coin per se, translations between the two models have been produced [24]; the stack-coin-age model represents an implementation of the UTXO coin-age model for account based on blockchains.

Each transaction spends output from prior transactions and generates new outputs that can be spent by transactions in the future as shown in Fig.1. All the unspent transactions are kept in each fully synchronized node. A user's wallet keeps track of a list of unspent transactions associated with all addresses owned by the user, and the balance of the wallet is calculated as the sum of those unspent transactions.

C. ANALYSIS METRICS AND APPROACH

In this study, the Pearson's correlation coefficient is used to investigate linear influences of each relevant feature of bitcoin on the price. The coefficient value lies between -1, 0, 1; a value of 1 indicates a perfect positive correlation, a value of -1 indicates perfect negative correlation while 0 indicates absolutely no correlation at all. The correlation coefficient is given by (1).

$$r = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

Scaling the correlated data for each metric between -1 and 1 cannot be accurately represented in a graph form. We rescale the data between the range [0,1]. The normalization value is calculated using (2).

$$z = \frac{x_i - min(x)}{max(x) - min(x)} \quad (2)$$

The purpose of this work is to separate on-chain metrics by determining those which can be used in more advanced predictive algorithms and those which should be discarded. A high correlation value between the price and a metric does not necessarily mean that a metric is a good candidate, but it invites a further look.

IV. DATA ANALYSIS

In this section, we give a comprehensive overview of the on-chain activities by categorising them into user, miner and exchange activities, and thereafter, we analyse each of these activities against the price in the bitcoin market. Finally, to understand the dynamics of bitcoin, we outline the results of our analysis by correlating these three data categories with the price and rate of change of price of bitcoin using a correlation coefficient. Table 1 gives a description of each of the data categories alongside the corresponding data.

TABLE 1. On-chain data description

Data Category	Data
User Activity	Block count, Transactions volume, Transaction rate, Block Height, Daily Active Addresses, Total Addresses, UTXO, Wallets Address (> 1, >10, >100)
Miner Activity	Hash rate, Difficulty, Miners Balance, Block Interval, Miners Revenue from fees, Miners Inflow, Miners Outflow, Miners to Exchanges
Exchange Activity	Exchange Balance, Exchange Withdrawals, Exchange Inflow, Exchange Outflow, Exchange NetFlow

A. ON-CHAIN DATA DESCRIPTION

Several on-chain metrics are considered as follows:

Average block size (MB): the size of a block agreed among all participants.

Transactions per block: average number of transactions per block.

Hash rate: estimated number of Tera (trillion) hashes per a second all miners.

Difficulty:The number of hashes required to mine a block.

Block count: The total number of blocks mined on the bitcoin network.

Block Height: the total number of blocks ever created and included in the primary blockchain.

Transaction rate: The total amount of transactions per second.

Transactions Volume: The total amount of coins transferred on-chain.

Exchange Inflow/Outflow - The total amount of funds flowing in and out of exchange wallets to non-exchange wallets.

Exchange Balance - The total amount of bitcoins held on known exchange wallets.

Exchange Withdrawals - The number of withdrawals from known exchange wallets.

Exchange Deposits - The number of deposits to known exchange wallets.

Miners Inflow Volume - The total amount of coins transferred to miner addresses.

Miners Outflow Volume - The total amount of coins transferred from miner addresses.

Total Miners Revenue - The total miner revenue is the fees plus newly minted coins.

Miners Balance - The total supply held in miner addresses.

Miners to exchanges - The total amount of coins transferred from miners to exchange wallets.

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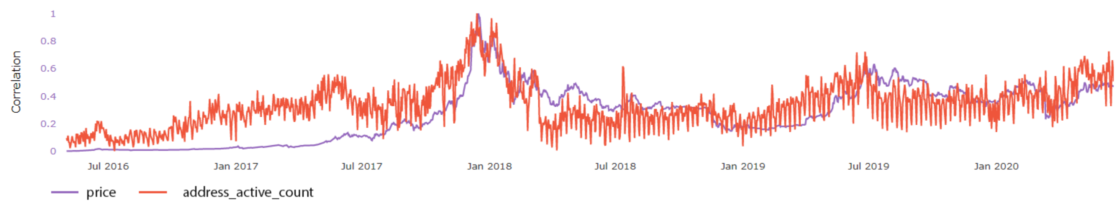

FIGURE 2. Correlation between prices and address active count.

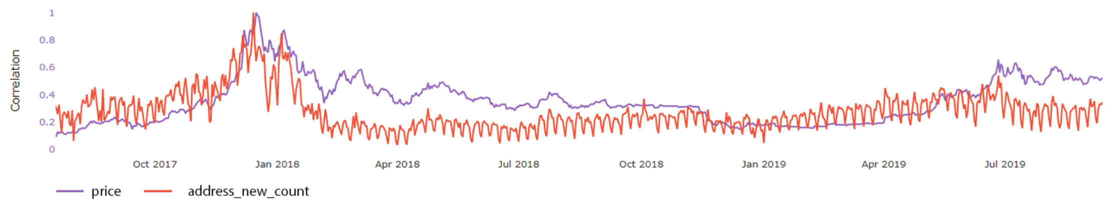

FIGURE 3. Correlation between prices and address new count.

Total Addresses – The total number of address indicates the usage of the bitcoin network since it first started in 2009.

Daily Active addresses - The number of active addresses in the network is the number of transactions sent and received on the network successfully.

Balances of Addresses - Total amount of coins held by a unique address

UTXO - Bitcoin employs the unspent transaction output (UTXO) record-keeping model, we can infer from the transactions, the age of each coin being circulated.

B. EFFECT OF USER ACTIVITY ON PRICE

In bitcoin, users can hold multiple unique addresses to send and receive bitcoins. The number of bitcoins in circulation, sentiment of the users among other activities could explain the reason behind bitcoin becoming more expensive and difficult to mine over time. In this section, we explain how the user activity, determined by highly correlated features, affects the price. Among them the features such as the number of wallets, the hash rate, and the UTXO's, determine the number of new users coming into the network, new miners joining the mining pools, and the aggregate spendable balance of all the users.

The maximum supply for bitcoins is around 21,000,000 [23] - max coins that can ever exist in the network. Since there are limited number of coins in the system, increase in the number of users in the network corresponds to greater demand resulting in increase in the price of bitcoin. The number of active addresses gives us an indication of the amount of users actively using the network to transfer funds from their wallets. While the number of active addresses directly indicate the network usage, the amount of funds going in and out of the blockchain network is equally an important metric to understand the network usage and in determining the bitcoin prices more accurately.

As mentioned earlier, we can infer the age of the coin using the UTXO's data in bitcoin and can be used to draw conclusions about the important price movements in bitcoin as seen in Fig. 2 and Fig. 5. For instance, if the aggregate age of the coin is high, it is an indication that more users are hodling their coins either as a long-term investment or to liquidate their assets when there's an increase in price. Conversely, if the aggregate age of the coin is low, it implies more number of users are actively sending and receiving coins from their wallets in the bitcoin network. Based on our observations above, we deduce that some of the important metrics including the number of unique addresses, active addresses, unspent transactions and transactions rate provides useful insights into user activities on the bitcoin network.

C. EFFECTS OF EXCHANGE ACTIVITY ON PRICE

In the early days, the only way people could buy and sell bitcoin was through online forums. This all changed in 2010 when bitcoinmarket.com was launched. This was the first exchange platform that allowed people to buy and sell bitcoins in exchange for USD. Since its launch in 2010, bitcoinmarket.com has been plagued with security issues and fraud, making its days numbered. Subsequently, Mt.Gox took over where bitcoinmarket.com left and dominated the market by becoming the world's largest bitcoin exchange operating up to 70 % of the global transactions of bitcoin market from 2011 to 2014 [18]. In early 2014 Mt.Gox suffered from security issues that allowed hackers to steal several thousands of bitcoins resulting in destabilization of the bitcoin market with the price plunging by 20%. After the impact of Mt.Gox on the bitcoin industry, altcoins emerged as a replacement to Gox with significant changes to the exchange practises amongst other issues transforming the bitcoin industry as a whole.

Bitcoin exchanges are comparable to a traditional stock

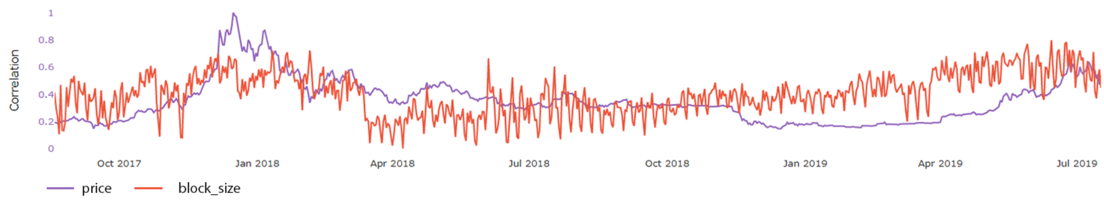

FIGURE 4. Correlation between prices and block size.

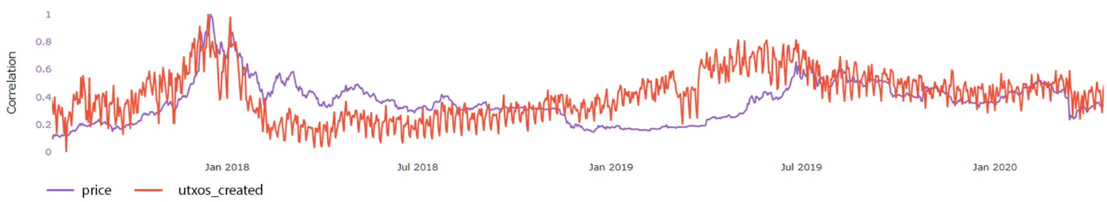

FIGURE 5. Correlation between prices and UTXO created .

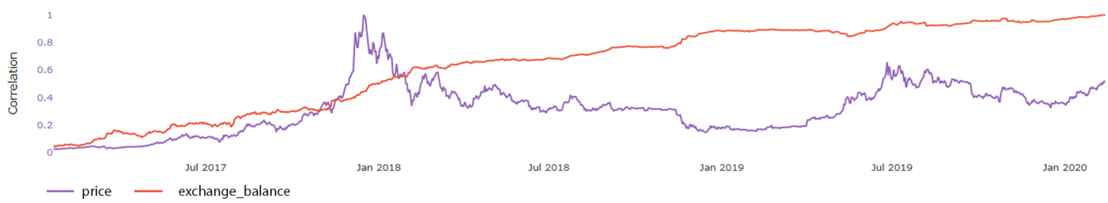

FIGURE 6. Correlation between prices and exchange balance.

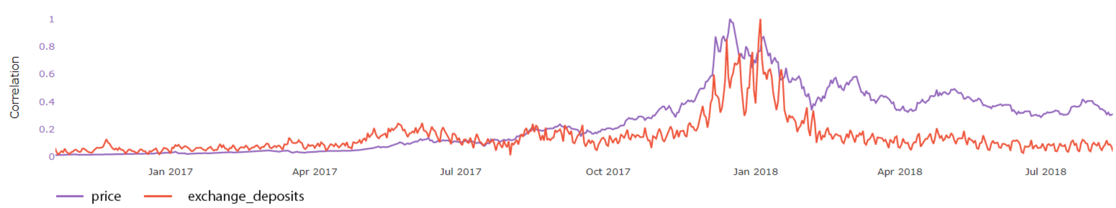

FIGURE 7. Correlation between prices and exchange deposits.

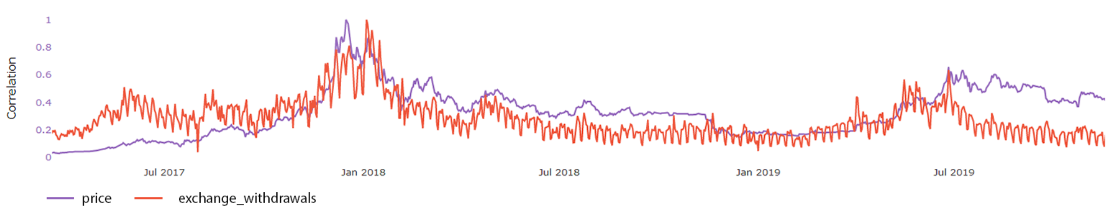

FIGURE 8. Correlation between prices and exchange withdrawals.

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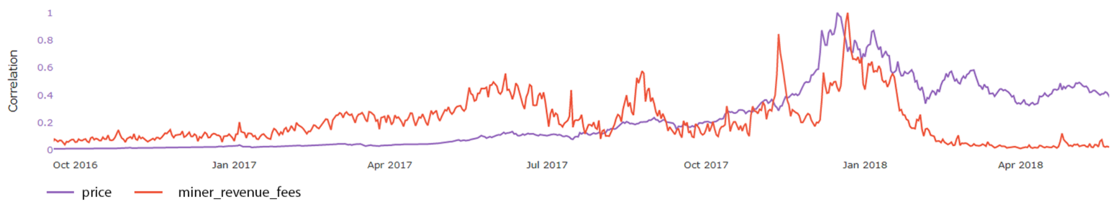

FIGURE 9. Correlation between prices and miner revenue from fees.

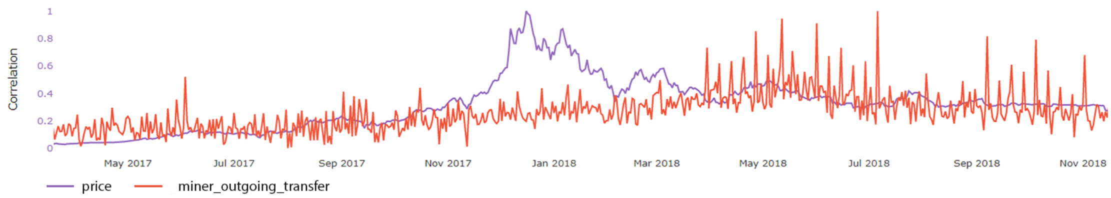

FIGURE 10. Correlation between prices and miners outgoing transfer.

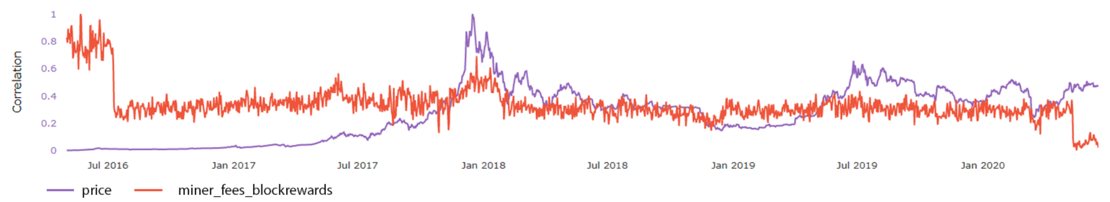

FIGURE 11. Correlation between prices and miner revenue from block rewards.

exchanges as they generate bitcoin as part of their services including transactions and fund transfer fees. At any given point, the exchanges can sell their revenue generated through fees on their own platform resulting in a significant amount of drop in bitcoin price. Large flow of funds to and from known exchange wallets amongst other factors can be an important indicator for predicting price volatility in the bitcoin market. Out of all 5 metrics, only 2 are highly correlated to the price.

However, there are periods of high correlation within these two years and analysing the reasons behind these correlations can help us uncover the state of bitcoin with the help of on-chain metrics. For example, between October 2017 and June 2018 (the period when the bull run was in full swing to the time the bear market was in its prime), exchange withdrawals were highly correlated to the price, with each month having a correlation value between 50 and 80%, with the exception of February 2018. This trend as captured in 8 represents the period of highest volatility, where the price had its most significant moves in both directions - from \$4000 in October 2017 up to \$20000 in December 2017 and back down to \$6000 in June 2018. We can also see that between May, June and July 2019 - while the price had a strong upward trajectory which has not been seen since late 2017, the correlation coefficient for exchange withdrawals was again high (around 60%). These two observations prompt the theory that when there is high volatility in the market, a knowledge of how many people withdraw from exchanges, and how that number changes over time can inform us about the direction of the price.

D. EFFECTS OF MINER ACTIVITY ON PRICE

Miners are the sole suppliers responsible for circulation of new coins in the market, hence it becomes extremely important to understand the miners behaviour patterns in order to understand the state of bitcoin. Overall, hashrate is at 150 exahash per second and currently there are 18,597,868 BTC in circulation [23], which is approximately 88.56% of the maximum supply of the coins that can ever exist in the bitcoin network.

Difficulty level is a value that is used to regulate the production of blocks which is approximately 10 minutes to add a new block into the bitcoin network. Over the last few years, bitcoin has gained immense popularity, with this growing incentive, more miners are likely to join the network, increasing the probability of solving the mathematical puzzle in less than 10 minutes. Hence, as the number of miners who participate in the network increases or decreases, so does the difficulty, the difficulty value adjusts every 2016 blocks to maintain the complexity level required to solve a mathematical puzzle in about 10 minutes, which explains the

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reason hash rate grows with the increase in price. This is another important metric of the inherent usage - and value - of the network.

As seen in the Fig. 11, in July 2016, a bitcoin halving event occurred - the mining reward is cut in half every four years- resulting in a reward of 12.5 BTC instead of 25 BTC. In Figs. 9 - 10, we observe from the miner fees that network participants pay to have their transactions minted, the higher the fee one pays, the faster their transaction will be validated by the pool of miners, and to cover operational costs, miners must sell their coins to liquidate their crypto-assets to cover their expenses, resulting in a sell pressure. Therefore, analyzing these patterns can help us understand the overall health of the bitcoin network.

TABLE 2. Mean correlation value for every on-chain metric between 2016 and 2020

Data Category	Mean Correlation
Block Count	0.593742
Block Size	0.393856
Transactions Volume	0.389275
Transactions rate	0.497482
Hash rate	0.365158
Difficulty	0.314971
Block Height	0.503446
Miners Revenue	0.334320
Miners Inflow	0.133533
Miners Outflow	0.061251
Miners Netflow	0.747033
Miners to exchanges	0.037683
Exchange Balance	0.553659
Exchange Withdrawls	0.228717
Exchange Inflow	0.158977
Exchange Outflow	0.015609
Exchange NetFlow	0.429214
Daily Active Address	0.331989
Total Address	0.479324
UTXO	0.386991
Addresses (> 1 coin)	0.587204
Addresses (> 10 coins)	0.621554
Addresses (> 100 coins)	0.454518

V. jSO OPTIMIZATION ALGORITHM

jSO algorithm is an extended version of iL-SHADE and iL-SHADE is an extended version of the L-SHADE, where L-SHADE algorithm is a Differential Evolution (DE)-based algorithm that uses a population linear reduction approach [25]. Mainly, DE has four main steps: initialization, mutation, crossover and selection operations. It also has three parameters: scaling factor (F), crossover rate (CR) and population size (NP). Determining the best combination of NP, F and CR is a challenging and time consuming task. Therefore, several self-adaptive techniques have emerged to find the best values of these parameters and one of them will be used in this paper [25]. In this section, the main components of jSO will be discussed in detail.

1) Initialization phase

In this phase, an initial population of size NP $p_0 = (\overrightarrow{x}_{1,0}, \overrightarrow{x}_{2,0}, ... \overrightarrow{x}_{NP,0})$ is randomly generated using Equation 3.

$$x_{i,j} = x_{i,j}^{min} + rand \times (x_{i,j}^{max} - x_{i,j}^{min}) \quad i = 1, 2, ..., NP \text{ and } j = 1,\ 2,\ ...,\ D \tag{3}$$

where NP refers to the population size, D the problem dimension (number of decision variables), and $x_{i,j}^{max}$, $x_{i,j}^{min}$ the upper and lower bounds of j^{th} decision variable.

2) Mutation Operator

After initialization, a mutation operator is used to produce a mutant solution. As per literature, there are many mutation strategies with various capabilities and characteristics [26]. Some of them are good for exploitation while others are good for exploration. The most popular mutation strategies are listed below.

- DE/best/1

$$\overrightarrow{v}_i^g = \overrightarrow{x}_{best}^g + F(\overrightarrow{x}_{r1}^g - \overrightarrow{x}_{r2}^g) \tag{4}$$

- DE/rand/1

$$\overrightarrow{v}_i^g = \overrightarrow{x}_{r1}^g + F(\overrightarrow{x}_{r2}^g - \overrightarrow{x}_{r3}^g) \tag{5}$$

- DE/current-to-best/1

$$\overrightarrow{v}_i^g = \overrightarrow{x}_i^g + F(\overrightarrow{x}_{best}^g - \overrightarrow{x}_i^g) + F(\overrightarrow{x}_{r1}^g - \overrightarrow{x}_{r2}^g) \tag{6}$$

- DE/current-to-pbest/1

$$\overrightarrow{v}_i^g = \overrightarrow{x}_{i,g} + F(\overrightarrow{x}_{pbest}^g - \overrightarrow{x}_i^g) + F(\overrightarrow{x}_{r1}^g - \overrightarrow{x}_{r2}^g) \tag{7}$$

where the indexes $r_1 \neq r_2 \neq r_3 \neq i$ and r_1, r_2, r_3 are random numbers generated in $[1, NP]$. i represents the current solution. g is the current generation, $\overrightarrow{x}_{best}$ the best solution in the current generation and $\overrightarrow{x}_{pbest}$ randomly selected solution from the top $p\%$ solutions.

jSO uses a new weighted mutation strategy, which is a modified version of the DE/current-to-pbest/1 mutation strategy as

$$\overrightarrow{v}_i^g = \overrightarrow{x}_i^g + F_w(\overrightarrow{x}_{pBest}^g - \overrightarrow{x}_i^g) + F(\overrightarrow{x}_{r1}^g - \overrightarrow{x}_{r2}^g) \tag{8}$$

where F_w is a weighted version of the scaling factor F calculated by:

$$F_w = \begin{cases} 0.7 * F, nfes < \ 0.2 \times max_{fes}, \\ 0.8 * F, nfes < \ 0.4 \times max_{fes}, \\ 1.2 * F, \text{ otherwise}. \end{cases} \tag{9}$$

where $nfes$ and max_{fes} are the current and maximum number of function evaluations, respectively. The values of F are generated using the same technique proposed by Tanabe et al. [28]. These strategy apply a smaller factor F_w to multiply difference of vectors in which $\overrightarrow{x}^{g}_{pBest}$ appears at early stages of the evolutionary process, while in later stages higher factor F_w is used.

3) Crossover Operator

After mutation, a crossover operator is used for every mutant vector $\overrightarrow{v}_i$ to generate the trial/offspring vector $\overrightarrow{u}_i$. There are two main crossover operators, binomial and exponential [26] [27]. jSO algorithm uses the binomial crossover operator as

$$u^g_{i,j} = \begin{cases} v^g_{i,j}, & \text{if } rand(0,1) \le CR \text{ or } j = j_{rand}, \\ x^g_{i,j}, & Otherwise. \end{cases} \tag{10}$$

where $j_{rand} \in [1,\, 2,\, ...,\, D]$ and $rand \in [0,\, 1]$ are randomly chosen to ensure that at least one decision variable is gained from the trial vector and CR crossover rate used to control the number of variables are inherited from the donor vector. Similar to F, the values of CR are generated using the method proposed in [28].

4) Selection Operator

After mutation, a greedy selection is applied to decide which solution from the parent population ($\overrightarrow{x}^g_i$) and the trial population ($\overrightarrow{u}^g_i$) entering the next generation. If the fitness function value of the trial solution ($f(\overrightarrow{u}^g_i)$) is better than the value of the parent solution ($f(\overrightarrow{x}^g_i)$), then the trial solution enters the new population, otherwise the parent solution enters the new population, This process is mathematically carried out as:

$$\overrightarrow{x}^{g+1}_i = \begin{cases} \overrightarrow{u}^g_i, & \text{if } f(\overrightarrow{u}^g_i) \le f(\overrightarrow{x}^g_i), \\ \overrightarrow{x}^g_i, & \text{Otherwise.} \end{cases} \tag{11}$$

The main steps of the jSO algorithm are presented in Algorithm 1. jSO also uses a linear population size mechanism to update the number of individuals in the entire population at each generation [28]. This is done using:

$$NP^{g+1} = round[(\frac{NP^{min} - NP^{init}}{max_{fes}}) \times fes + NP^{init}] \tag{12}$$

where NP^{min} is the minimum number of individuals the algorithm can use, fes the current number of function evaluations (fes), max_{fes} the largest number of fes.

Algorithm 1 jSO algorithm

Define $g \leftarrow 0$, $A \leftarrow \{\}$;
Generate an initial random population (P_0) of size NP;
Evaluate $f(P_0)$, and update number of fitness evaluations $fes \leftarrow fes + NP$;
while $fes \le max_{fes}$ **do**
  $g \leftarrow g + 1$;
  for $i = 1 : NP$ **do**
    Generate mutant solution ($\overrightarrow{v_i}^g$) using Equation 8;
    Apply crossover to generate offspring solution ($\overrightarrow{u_i}^g$) using Equation 10;
    Evaluate new population $f(\overrightarrow{u_i}^g)$
  end for
  for $i = 1 : NP$ **do**
    if $f(\overrightarrow{u}^g_i) \le f(\overrightarrow{x}^g_i)$ **then**
      $\overrightarrow{x}^{g+1}_i \leftarrow \overrightarrow{u}^g_i$;
    else
      $\overrightarrow{x}^{g+1}_i \leftarrow \overrightarrow{x}^g_i$;
    end if
    if $f(\overrightarrow{u}^g_i) < f(\overrightarrow{x}^g_i)$ **then**
      $x^g_i \rightarrow A$;
      Update F and Cr as in [28], and F_w as in Equation 9;
    end if
    Update A if needed;
    Apply linear population size reduction technique as in Equation ;
  end for
end while

A. LONG SHORT-TERM MEMORY (LSTM) MODEL

Long short-term memory (LSTM) is a special form of recurrent neural networks (RNNs), that has a robust and an efficient capacity to solve long-term and short-term dependency problems. The memory cell is the cornerstone of LSTM network, which replaces the hidden layers of the conventional neurones. As the LSTM has three gates (input, output and forget gates, it has the ability to add or remove information to the state of the cell. The process of updating the cell state and calculating the output of the LSTM model are computed by:

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}C_{t-1} + b_i) \tag{13}$$

$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}C_{t-1} + b_f) \tag{14}$$

$$c_t = f \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \tag{15}$$

$$O_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}C_{t-1} + b_o) \tag{16}$$

$$m_t = O_t \odot h(c_t) \tag{17}$$

$$y_t = W_{ym}m_t + b_y \tag{18}$$

where x_t and y_t are the input and output data at time t, respectively. i_t, o_t and f_t are the input, output and forget gates at time t, respectively, m_t the vector of activation of every memory block and c_t the vector of activation of every cell. σ, g and h denote gate, input, and output activation functions. W represents the weight coefficients.

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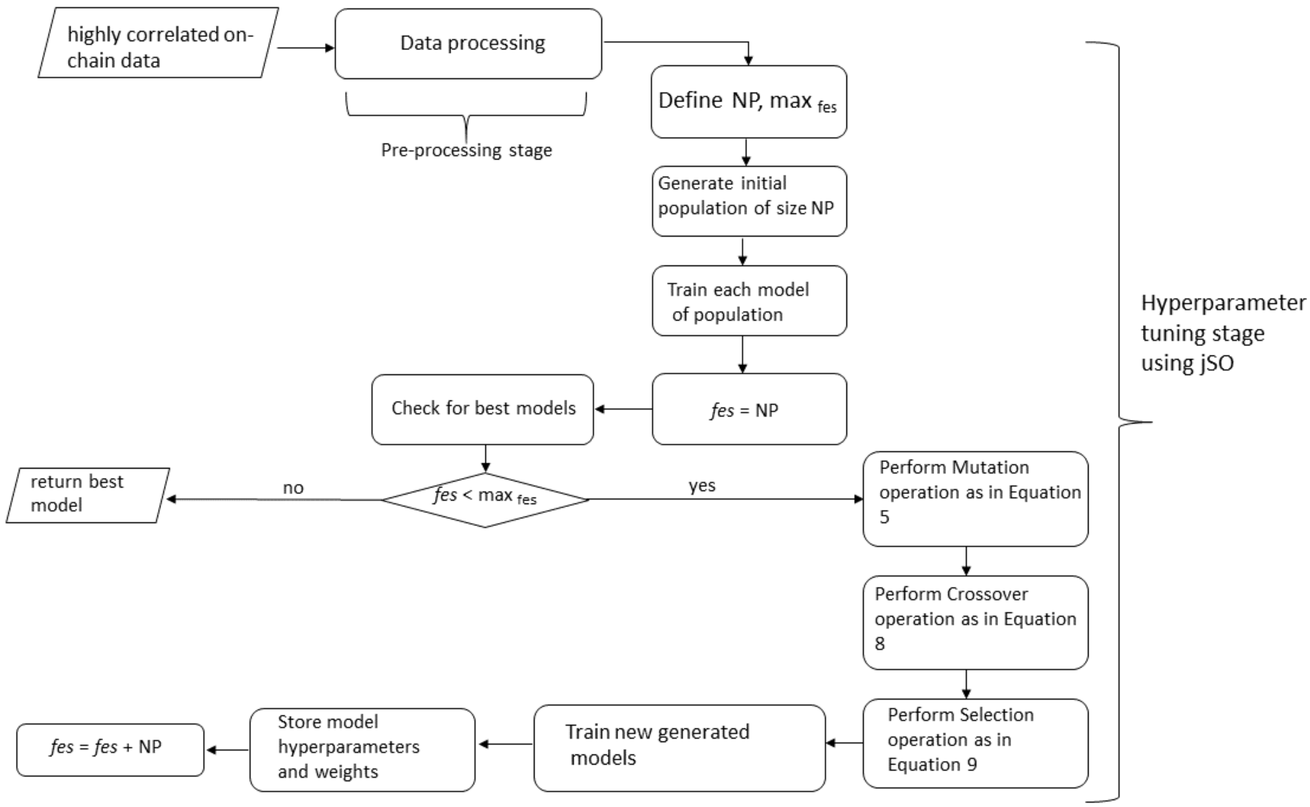


FIGURE 12. The proposed CNN-jSO flow chart

B. jSO-BASED OPTIMIZATION OF LSTM MODEL

This section introduces the use of jSO algorithm to determine the structure and hyper-parameters values of LSTM model. In the literature, setting the best values of the hidden layers number and number of related neuron in each of the hidden layer is a challenging task. This process was done using trial and error, but it consumes a huge a mount of time and resources, and can not be effectively used. Also, the prediction ability of LSTM is highly dependent on the number of hidden layers and number of neurons in each layer. As a result, jSO algorithm is utilized as an optimizer used to optimize the hidden layers number (n_{hl}) and its corresponding number of neurons (n_n) and at the same time to minimize the loss function.

The main steps of the proposed jSO-LSTM are described as follows:

Input: The lower and upper bounds of related parameters that required by jSO algorithm.

Output: The best hidden layers numbers and number of neurons in each hidden layer.

Step 1: Generate an initial population (P_0) of size NP, which represents different number of hidden layers and different number of neurons, $P = (\overrightarrow{X}_{1,t}, \overrightarrow{X}_{2,t}, ..., \overrightarrow{X}_{NP,t})$ where t is the iteration number, NP the population size, and $\overrightarrow{X}_{i,t} = (x_{i,1,t}, x_{i,2,t}, ..., x_{i,D,t})$ is the ith solution at iteration t and D is the number of variables.

Step 2: Compute the objective function value, $f(\overrightarrow{X}_{i,t})$, (loss function) of each solution in P_0. To do this, the LSTM model is built for each solution and the loss function of the training step is calculated.

Step 3: Generate a mutant vectors, $V = (\overrightarrow{v}_{1,t}, \overrightarrow{v}_{2,t}, ..., \overrightarrow{v}_{NP,t})$ as described in Section V-2.

Step 4: Generate an offspring solutions, $U = (\overrightarrow{u}_{1,t}, \overrightarrow{u}_{2,t}, ..., \overrightarrow{u}_{NP,t})$ as described in Section V-3.

Step 5: Compute the objective function value, $f(\overrightarrow{u}_{i,t})$, (loss function) of each generated solution.

Step 6: Perform the selection operator as described in Section V-4.

Step 7: Update number of epochs (iterations) $t \leftarrow t + 1$.

Step 8: If the stopping condition is met, return the best numbers of hidden layers and number of neurons in each of the hidden layers of the LSTM model, and the corresponding loss function value of the best model. Otherwise go to **step 3**. These steps are depicted in the flow chart shown in Fig.12

VI. EXPERIMENTAL SETUP

The proposed model is applied on the highly correlated on-chain dataset in order to predict the price of the bitcoin. The description of this data set is given in Section VI.

The proposed CNN-jSO was implemented using Python 3.7.6 and the TensorFlow application programming interface

(TF-API). The training process were performed on Google Colab with Tensor Processing unit (TPU). Training and hyperparameters tuning using jSO. Using jSO to tune the 17 hyperparameters which are involved in building the architecture of the network. The proposed algorithm generated 198 different models, each of which has a different combination of parameters to be trained and evaluated. The best combination of parameters with the smallest loss value is chosen for developing a prediction model for bitcoin.Table 3 shows the full set and ranges of the hyperparameters.

TABLE 3. Lower and upper bounds of Hyperparameters

Hyperparameters	Min	Max
No. of LSTM layers	2	4
LSTM 1	8	64
Recurrent Dropout in Layer 1	30	40
LSTM 2	32	128
Recurrent Dropout in Layer 2	30	50
LSTM 3	86	256
Recurrent Dropout in Layer 3	30	50
LSTM 4	86	256
Recurrent Dropout in Layer 4	30	50
Dropout between LSTM and Dense layers	30	50
Number of Dense layers	0	5
Number of neurons in each dense Layer		
Layer 1	256	512
Layer 2	128	256
Layer 3	64	128
Layer 4	32	64
Layer 5	16	32

VII. RESULTS AND ANALYSIS

In this section, we present the results of our research and also provide a detailed analysis of these results. Following our classification of the on-chain metrics and correlation of these metrics with the price of bitcoin in Section IV, the output obtained was used to develop a deep learning model. This was achieved by employing a self-adaptive technique called the the jSO optimization algorithm. This choice of the jSO algorithm was informed owing to its distinct ability to very quickly return the best model parameters that are able to predict and closely follow the real price of bitcoin with very high accuracy. Table 4 represents the best combinations of parameters obtained from the proposed algorithm. These parameters give us the least error rate for predicting the price of bitcoin.

The graph in Fig.13, shows a plot of the predicted price of bitcoin using the jSO optimisation algorithm when compared with the real price of bitcoin over a given period. It is observed that the predicted price of bitcoin compares very closely with the actual price. This is possible because our model employs a holistic approach by taking into account the behavioural patterns not only from user activities but from miners and exchanges as well. Since users can sell or buy bitcoins, miners and exchanges also earn bitcoins in the form of reward or transaction fees. At some point, they (miners and exchanges) will also have to sell coins to cover their expenses, resulting in sell pressure. These data which are available on-chain are then correlated with price and only the most significant/highly correlated metrics are fed into the jSO algorithm for predicting the price of bitcoin. Using this technique, our jSO-based LSTM model is able to obtain a higher accuracy and better price match when compared with other prediction models such as the traditional LSTM model.

TABLE 4. The best Hyperparameters obtained by jSO

Hyperparameters	Value
No. of LSTM layers	3
LSTM 1	10
Recurrent Dropout in Layer 1	31
LSTM 2	90
Recurrent Dropout in Layer 2	35
LSTM 3	230
Recurrent Dropout in Layer 3	41
LSTM 4	150
Recurrent Dropout in Layer 4	37
Dropout between LSTM and Dense layers	41
Number of Dense layers	5
Number of neurons in each dense Layer	
Layer 1	377
Layer 2	161
Layer 3	105
Layer 4	43
Layer 5	23

To buttress this point, we carried out a mean absolute error (MAE) analysis between the jSO-based LSTM and the LSTM models. The formula for the MAE is given as:

$$MAE = \frac{1}{n}\sum_{s=1}^{n}|y_s - \hat{y_s}| \tag{19}$$

where n is the number of data points and y_s and $\hat{y_s}$ are the real and predicted prices of sth point.

TABLE 5. Mean Absolute Error(MAE) for LSTM and LSTM-jSO at different training sizes

Train Size	MAE	
	LSTM	LSTM-jSO
0.1	4.0567	2.06088
0.5	3.0542	2.04965
0.9	2.9035	1.89352

The results of the analysis are presented in Table 5. It can be seen that for different training sizes of 0.1, 0.5 and 0.9, the jSO-based LSTM model gives lower MAE values corresponding to a 49.2 %, 32.9 % and 34.8 % improvement respectively over the LSTM model counterpart. This suggests that our model can be used as a tool to provide quicker and highly accurate prediction of bitcoin prices.

VIII. CONCLUSION AND FUTURE WORKS

In this article, we evaluate the price of bitcoin through a correlation analysis with various on-chain metrics, exemplified by bitcoin. We classify the collected on-chain data to understand the dynamics of bitcoin and assess the most significant metrics that influences the price of bitcoin. We use our findings to develop a machine learning model that

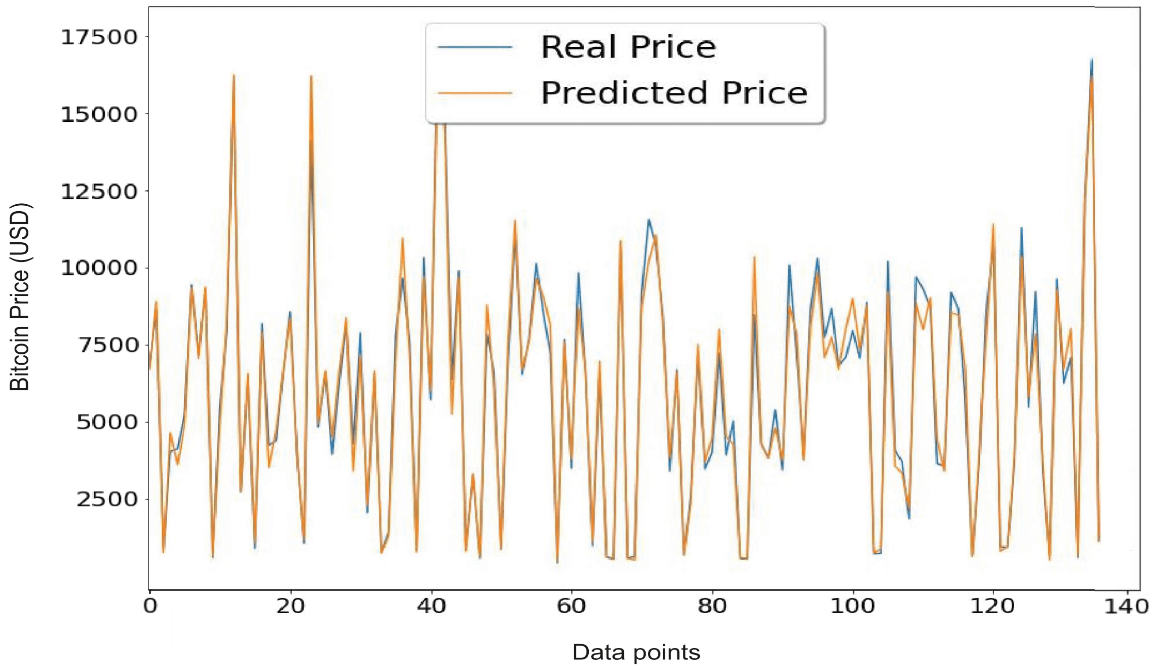


FIGURE 13. Real Price vs Predicted Price using jSO optimization algorithm.

uses a self-adaptive technique to find the best values of the parameters in-order to accurately predict the price of bitcoin. Compared to the previous work that predicts by using the historical prices of bitcoin and other attributes like global crude oil, fiat currencies, our approach uses a profusion of datasets that represent core activities related to bitcoin network including users, miners and exchanges and using jSO algorithm enables us to obtain highly accurate prediction rates with minimum error rate.

In future work, deep learning models can be further optimised using other self-adaptive techniques and correlating them to price and behaviour of crypto assets to further improve the prediction rate for bitcoin.

REFERENCES

[1] X. Xiang, M. Wang and W. Fan, "A Permissioned Blockchain-Based Identity Management and User Authentication Scheme for E-Health Systems," in IEEE Access, vol. 8, pp. 171771-171783, 2020, doi: 10.1109/ACCESS.2020.3022429.

[2] "Bitcoin: A peer-to-peer electronic cash system", 2008. [Online]. Available: http://bitcoin.org/bitcoin.pdf.

[3] C. Lee, [ann] litecoin - a lite version of bitcoin, 2011, [online] Available: https://bitcointalk.org/index.php?topic=4741.

[4] Eross, Andrea McGroarty, Frank Urquhart, Andrew Wolfe, Simon, 2019."The intraday dynamics of bitcoin," Research in International Business and Finance, Elsevier, vol. 49(C), pages 71-81

[5] Brauneis, Alexander Mestel, Roland, 2018. "Price discovery of cryptocurrencies: Bitcoin and beyond," Economics Letters, Elsevier, vol. 165(C), pages 58-61.

[6] R. Hudson, A. Urquhart, 7402298418;57214699137; "Technical trading and cryptocurrencies," *Annals of Operations Research*, (2019)

[7] J. Huang, W. Huang, J. Ni, "Predicting bitcoin returns using high-dimensional technical indicators," *The Journal of Finance and Data Science*,Volume 5, Issue 3, 2019,Pages 140-155,ISSN 2405-9188,https://doi.org/10.1016/j.jfds.2018.10.001.

[8] H. Jang and J. Lee, "An Empirical Study on Modeling and Prediction of Bitcoin Prices With Bayesian Neural Networks Based on Blockchain Information," in IEEE Access, vol. 6, pp. 5427-5437, 2018, doi: 10.1109/ACCESS.2017.2779181.

[9] L. Kristoufek, “Bitcoin meets Google trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era,” Sci. Rep., vol. 3, p. 3415, Dec. 2013.

[10] S. Kamrat, N. Suesangiamsakul and R. Marukatat, "Technical Analysis for Cryptocurrency Trading on Mobile Phones", 2018 3rd Technology Innovation Management and Engineering Science International Conference (TIMES-iCON), Bangkok, Thailand, 2018, pp. 1-4.

[11] S. McNally, J. Roche and S. Caton, "Predicting the Price of Bitcoin Using Machine Learning," 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP), Cambridge, 2018, pp. 339-343

[12] A. Shynkevich, "Bitcoin Futures, Technical Analysis and Return Predictability in Bitcoin Prices," *Journal of Forecasting*, 2020. [online]. Avalaible: https://doi.org/10.1002/for.2656

[13] M. Bartoletti, S. Lande, L. Pompianu, and A. Bracciali, “A general framework for blockchain analytics,” in *Proc. Workshop on Scalable and Resilient Infrastructures for Distributed Ledgers*, ACM, 2017, pp. 1–6. DOI: 10.1145/3152824.3152831

[14] McGinn, D. McIlwraith, D Guo, Y.. (2018). Toward Open Data Blockchain Analytics: A Bitcoin Perspective. Royal Society Open Science. 5. 10.1098/rsos.180298.

[15] A. Balaskas and V. N. Franqueira, “Analytical tools for blockchain: Review, taxonomy and open challenges," in *Proc. Conference on Cyber*

Security and Protection of Digital Services (Cyber Security), IEEE, 2018, pp. 1–8. DOI:10.1109/CyberSecPODS.2018.8560672.
[16] D. N. Dillenberger et al., "Blockchain analytics and artificial intelligence," in IBM Journal of Research and Development, vol. 63, no. 2/3, pp. 5:1-5:14, March-May 2019, doi: 10.1147/JRD.2019.2900638.
[17] M. Saad and A. Mohaisen, "Towards characterizing blockchain-based cryptocurrencies for highly-accurate predictions," *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, Honolulu, HI, 2018, pp. 704-709, doi: 10.1109/INFCOMW.2018.8406859.
[18] M. Saad, J. Choi, D. Nyang, J. Kim and A. Mohaisen, "Toward Characterizing Blockchain-Based Cryptocurrencies for Highly Accurate Predictions," in *IEEE Systems Journal*, vol. 14, no. 1, pp. 321-332, March 2020, doi: 10.1109/JSYST.2019.2927707.
[19] "Bitcoin block explorer - blockchain", 2018, [online] Available: https://blockchain.info/.
[20] "Santiment". Accessed:12- Dec- 2020. [online] Available:https://app.santiment.net/
[21] Glassnode Studio - On-Chain Market Intelligence.Accessed: 1- Aug-2020. [online] Available: https://studio.glassnode.com/
[22] "SegWit, explained". Accessed:15- Nov- 2020. [online] Available:https://cointelegraph.com/explained/segwit-explained
[23] "The bitcoin.com wallet". Accessed:15- Nov- 2020. [online] Available: https://markets.bitcoin.com/crypto/BTC
[24] Zahnentferner, Joachim: Chimeric Ledgers: Translating and Unifying UTXO-based and Account-based Cryptocurrencies https://eprint.iacr.org/2018/262.pdf
[25] J. Brest, M. S. Maucec, and B. Boškovi ˘ c, “Single objective real-parameter ´ optimization: Algorithm jso,” in 2017 IEEE congress on evolutionary computation (CEC). IEEE, 2017, pp. 1311–1318.
[26] K. M. Sallam, S. M. Elsayed, R. K. Chakraborrty, and M. J. Ryan, “Evolutionary framework with reinforcement learning-based mutation adaptation,” IEEE Access, 2020.
[27] K. M. Sallam, S. M. Elsayed, R. K. Chakrabortty, and M. J. Ryan, “Improved multi-operator differential evolution algorithm for solving unconstrained problems,” in 2020 IEEE Congress on Evolutionary Computation (CEC). IEEE, 2020, pp. 1–8.
[28] R. Tanabe and A. S. Fukunaga, “Improving the search performance of shade using linear population size reduction,” in 2014 IEEE congress on evolutionary computation (CEC). IEEE, 2014, pp. 1658–1665.

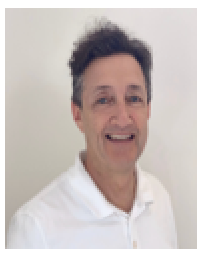
NISHANT JAGANNATH is currently pursuing a PhD degree at the University of Canberra, Australia. His doctoral research investigates the current issues in adopting blockchain technology, given the diverse nature of its implementations from financial markets to supply chain. He holds a Master’s degree in Network Engineering and is also a part-time faculty member in the Science Technology department at the University of Canberra. His research interests include integrating blockchain technology with the Internet of things (IoT) and cyber-physical systems.

TUDOR BARBULESCU holds a BIT from the Australian National University and is currently pursuing a Masters in Computing / Business Informatics from the University of Canberra. Recently he has been working as a software developer on personal projects and for clients and his interest lies at the intersection of algorithmic trading and blockchain. Before this he co founded an augmented reality startup.

KARAM M. SALLAM received the Ph.D. degree in computer science from the University of New South Wales at Canberra, Australian Force Academy, Canberra, Australia, in 2018. He is currently a Lecturer at Zagazig University, Zagazig, Egypt. His current research interests include evolutionary algorithms and optimization, constrained-handling techniques for evolutionary algorithms, operation research, machine learning, deep learning, Cybersecurity and IoT. He was the winner of IEEE-CEC2020 competition. He serves as an organizing committee member of different conferences in the evolutionary computation field. and a reviewer for several international journals.

IBRAHIM ELGENDI (M’16)holds a PhD in Information Technology from University of Canberra, Australia. He is currently the lecturer in Networking and Cybersecurity. He is a member of the Institution of Engineers Australia, His research focuses on Mobile and Wireless Networks, Internet-of-Things, Machine Learning, and Cyber-Physical-Security. Dr. Elgendi has over 14 refereed publications with over 63 citations (H-index 5) in highly prestigious journals, and conference proceedings. He has served as a reviewer for a number of journals such as IEEE Wireless Communications magazine, IEEE Transaction on Mobile Computing, and IEEE/ACM Transactions on Networking. He has 17 years’ experience from industry in the field of Automation and AI.

ASUQUO A. OKON (S’20) received the Bachelor of Engineering degree in electrical and computer engineering from the Federal University of Technology, Minna, Nigeria, in 2006 and the Master of Science degree with distinction in telecommunications electronics from the University of Glasgow, United Kingdom, in 2012. Between 2012 and 2017, he held the position of Senior Research Engineer at The National Space Research and Development Agency, Nigeria. He is currently pursuing the PhD degree with the School of IT and Systems at the University of Canberra, Australia. His research interests include Software Defined Networks, Blockchain, Internet of Things and resource allocation and optimization techniques in beyond 5G networks.



BRADEN MCGRATH is a Research Professor at Embry-Riddle Aeronautical University and the CEO of Cann Pharmaceutical Australia. Braden is a Chartered Engineer in the Engineers Australia Colleges of Biomedical Engineering and Leadership and Management; a Fellow of Engineers Australia; a QinetiQ Fellow; a member of the Society of Flight Test Engineers; and a certified Sports Medicine Trainer. Braden holds a Ph.D. in Aeronautical Engineering from the University of Sydney and a Master’s in Aeronautics and Astronautics from MIT and his current research activities include the development of secure supply chain technology for pharmaceutical-quality medicinal cannabinoid drug development on the human neurological system.

ABBAS JAMALIPOUR (S'86–M'91–SM'00–F'07) is the Professor of Ubiquitous Mobile Networking at the University of Sydney, Australia, and holds a PhD in Electrical Engineering from Nagoya University, Japan. He is a Fellow of the Institute of Electrical, Information, and Communication Engineers (IEICE) and the Institution of Engineers Australia, an ACM Professional Member, and an IEEE Distinguished Lecturer. He has authored nine technical books, eleven book chapters, over 450 technical papers, and five patents, all in the area of wireless communications. Dr. Jamalipour is the President and an elected member of the Board of Governors of the IEEE Vehicular Technology Society. He was the Editor-in-Chief IEEE Wireless Communications, Vice President-Conferences and a member of Board of Governors of the IEEE Communications Society, and serves as an editor of IEEE Access, IEEE Transactions on Vehicular Technology, and several other journals. He has been a General Chair or Technical Program Chair for a number of conferences, including IEEE ICC, GLOBECOM, WCNC and PIMRC. He is the recipient of a number of prestigious awards such as the 2019 IEEE ComSoc Distinguished Technical Achievement Award in Green Communications, the 2016 IEEE ComSoc Distinguished Technical Achievement Award in Communications Switching and Routing, the 2010 IEEE ComSoc Harold Sobol Award, the 2006 IEEE ComSoc Best Tutorial Paper Award, as well as 15 Best Paper Awards.

KUMUDU MUNASINGHE holds a PhD in Telecommunications Engineering from University of Sydney. He is currently the Associate Professor in Network Engineering, leader of the IoT Research Group at the Human Centred Research Centre, University of Canberra. His research focuses on Next Generation Mobile and Wireless Networks, Internet-of-Things, Green Communication, Smart Grid Communications, and Cyber-Physical-Security. A/Prof Munasinghe has over 100 refereed publications with over 900 citations (H-index 17) in highly prestigious journals, conference proceedings and two books to his credit. He has secured over $ 1.6 Million dollars in competitive research funding by winning grants from the Australian Research Council (ARC), the Commonwealth and State Governments, Department of Defence, and the industry. He has also won the highly prestigious ARC Australian Postdoctoral Fellowship, served as a co-chair for many international conferences, served as an editorial board member for a number of journals. A/Prof Munasinghe's research has been highly commended through many research awards including two VC's Research Awards and three IEEE Best Paper Awards. He is currently a Member of the IEEE, a Charted Professional Engineer, an Engineering Executive and a Companion (Fellow Status) of Engineers Australia.