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Research paper

Assessing machine learning performance in cryptocurrency market price prediction

Kamran Pakizeh[1], Arman Malek[2], Mahya Karimzadeh[3], Hasan Hamidi Razi[4]

[1] Faculty of Financial Sciences, Kharazmi University, Tehran, Iran
k.pakizeh@khu.ac.ir

[2] Faculty of Financial Sciences, Kharazmi University, Tehran, Iran
aarmancad@gmail.com

[3] Faculty of Financial Sciences, Kharazmi University, Tehran, Iran
mkarimzadeh1375@gmail.com

[4] Department of Hydraulics Engineering, Tarbiat Modares University, Tehran, Iran
hassan.hamidirazi@gmail.com

Abstract:
Cryptocurrencies, which are digitally encrypted and decentralized, continue to attract attention of financial market players across the world. Because of high volatility in cryptocurrency market, predicting price of cryptocurrencies has become one of the most complicated fields in financial markets. In this paper, we use Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models to predict price of four well-known cryptocurrencies of Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP). These models are subdivisions of Artificial Intelligence, machine learning and data science. The main aim of this paper is to compare the accuracy of above-mentioned models in forecasting time series data, to find out which model can better predict price in these four cryptocurrencies. 43 variables consisting of 28 technical indicators and t+10 lags were calculated and appended to the Open, High, Low, Close and Volume (OHLCV) data for selected cryptocurrencies. Applying random forest as feature selection, 25 variables were chosen, 24 of them selected as feature (independent variables) and one as a dependent variable. Each attribute value was converted into a relative standard score, followed by Min-max scaling; we compare models and results of Dieblod Mariano test that is used to examine whether the differences in predictive accuracy with these two models are significant, reveal that LSTM reaches better accuracy than GRU for BTC and ETH, but both models convey the same accuracy for LTC and XRP.

Keywords: Cryptocurrency, Long short-term memory, Gated recurrent unit, Random forest classifier.
JEL Classifications: E51, E42, E31.

1 Introduction

Hosting a network-based digital exchange medium, a cryptocurrency secures the records using strong cryptographic algorithms such as Secure Hash Algorithm 2 (SHA-2) and Message Digest 5 (MD5) [1]. Today, financial industry is experiencing

[3]Corresponding author

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rapid changes through cryptocurrencies as a new investment interface. The exogenous social and psychological factors affect their price prediction that has been a very challenging task for researchers so far. There exist three conventional approaches for cryptocurrencies price prediction: technical analysis, traditional time series forecasting, and machine learning method. A technical indicator is a time series that is obtained from mathematical formula(s) applied to another time series, which is typically a price [2]. Technical analysis uses only the price to predict future price movements [3]. This approach studies the effect of price movement. Technical analysis mainly uses open, high, low, close, and volume data to predict market direction or generate sell and buy signals [4]. It is based on the following three assumptions [5]: Market action discounts everything. Price moves in trends. History repeats itself. Technical indicators can be applied to anything that can be traded in an open market (e.g., stocks, futures, commodities, and cryptocurrencies). They are empirical assistants that are widely used in practice to identify future price trends and measure volatility [6]. By analyzing historical data, they can help forecast the future prices, moreover they are available at large numbers and used mostly by traders. We will select and use some of the indicators to create features in the existing data set. The technical indicators used in this study are described in Table 6.

Earlier classical regression techniques and Traditional time-series models such as ARIMA, SARIMA, ARCH, and GARCH are occasionally used to foresee price trends. Neural networks, currently, have come up with favorable outcomes in time-series data prediction; the ability to remember and extract the temporal specifications of data has led to emerging different neural networks to analyze cryptocurrency prices. Incorporating technical analysis, Artificial neural networks (ANN), which are a popular and more recent method, have been widely employed for the prediction of stock or cryptocurrency price fluctuations. Every algorithm has its specific learning patterns and subsequent prediction methods. Artificial neural network (ANN) algorithms act as a cornerstone for deep learning (DL) which is an advanced technique of machine learning (ML). Resembling an optimistic version of artificial intelligence, DL has drawn much attention over the last few years. Huang et al. [7] presented a daily buying/selling strategy for the Standards & Poors 500 Index and compared the performance of LSTM, GRU, ANN and SVM models. Sethia and Raut [8] exhibited that meaningful information can be effectively extracted from noisy financial time series data by LSTM network. In comparison with random forests, standard deep nets, and logistic regression, DL is a method of choice with respect to both predicational accuracy and daily returns after transaction costs [9].

Comparing different models comprising simple linear regression like ARIMA, AR, ARMA, or nonlinear models of ANN, ARCH, RNN, LSTM, Ghosh et al. [10] concluded that LSTM competently begets higher accuracy in comparison with other models. Forecasting stock market needs a nonlinear dynamic system; nonlinear inputoutput pairs enable LSTM to train themselves. In addition, much higher accuracy can be achieved by combining qualitative factors such as international events, financial news, News headlines sentiments, etc. [11]. Qiu et. al., [12] processed stock data through a wavelet transform and used an attention-based LSTM neural network to predict the stock opening price, compared the results with the other three models, including the LSTM model, the LSTM model with wavelet denoising and the gated recurrent unit (GRU) neural network model on S&P 500, DJIA, and HSI datasets. Focusing on just two cryptocurrencies, i.e., Litecoin and Monero, a LSTM and GRU-based hybrid cryptocurrency forecasting scheme has been put forward [1]. The inclusion of dual and single volatility to backpropagation neural networks to estimate XEO option price shows that the former outperforms the latter in ANN volatility models [13].

Deep learning methods have gained immense importance in price forecasting with their role in developing financial market and assisting traders to expand their trading strategies; moreover, they have approved their better performance in price forecasting against other method. Because cryptocurrency is a neoteric market and cryptocurrencies are novel financial instrument, therefore limited studies have been implemented in the field of predicting prices. This study examines and compares the prediction performance of two artificial neural networks for four cyptocurrencies; in addition we adopt technical indicators to our models in order to increase the accuracy of our prediction, combined with deep learning methods that our final feature incorporates 24 features which are selected by random forest from a set of variables including 28 technical indicators (listed in Table 6), t+10 lag of close price besides OHLCV data of selected cryptocurrencies. Considering that researchers have recently interested in price forecasting by two artificial neural networks LSTM and GRU [14] [12], thus this study deal with comparing their prediction accuracy. It is hypothesized that LSTM generates results with higher accuracy than GRU, because GRU has two gates, reset and update gates compared to LSTM having three gates, input, forget and output. GRU does not have an output gate and the update gate in GRU does the work of input and forget gate of LSTM. LSTM maintains an internal memory state cell, while GRU does not have a separate memory cell [8]. Our final result for BTC and ETH reveals the precedence of LSTM in price forecasting over GRU, while they showed equal accuracy in predicting price of LTC and XRP.

The article continuation structure is as follows: section 2 presents the literature of cryptocurrencies, neural networks and deep learning. Section 3 presents methodology, and section 4 includes experimental result. Section 5 describes conclusion and future research.

2 Literature review

2.1 Summary of cryptocurrency

In 2008, an anonymous researcher named Satoshi Nakamoto unveiled a paper entitled Bitcoin: A Peer-to-Peer (P2P) Electronic Cash System with the concept of P2P cash transfer of online payments without the involvement of any intermediary financial institutions [15]. He demonstrated the idea of a decentralized chain of valid transactions (chain of blocks), which are distributed among all peers in the network. It can be implemented using the proof-of-work (Pow) consensus mechanisms based on time stamps and hashes. A Pow algorithm is extensively used to validate the transaction and generate a new block in the chain. This P2P distributed system eliminates the trust and transparency issues of the traditional financial system, as no third party is involved in the execution of a transaction. It is transparent in nature as the chain is distributed to all nodes or peers. This conceptualizes the new form of the digital currency known as cryptocurrency. The price of the cryptocurrency has been a subject of curiosity for researchers across the globe. Cryptocurrencies prices are volatile and dependent on various factors such as transaction cost, mining difficulty, market trends, popularity, price of alternate coins, stock markets, sentiments, and some legal factors [16]. The aforementioned factors make the cryptocurrency prices unstable, which change rapidly over time and also make their prediction difficult. Hence, forecasting has been a very challenging and crucial task for the researchers.

Nowadays, cryptocurrencies have become a global phenomenon and attracted a significant number of users. Due to the properties like decentralization, immutability, a privacy coin owing to its transactions which are untraceable, unlikable, and analysis resistant and security, the cryptocurrencies show a promising future. Due to these characteristics, it is highly likely that their demand will increase in future. But the prices of cryptocurrencies are fluctuating a lot depending upon the parameters discussed above. Forecasting creates a matter of concern for researchers around the world. As per the literature, many researchers have tried machine learning and deep learning algorithms for cryptocurrencys price prediction [1]. Teker et al. [17] mapped the relation between changes in gold and oil prices and daily prices of Bitcoin, Tether, Ethereum, and Litecoin. Li et al. [18] predicted the global computing power of blockchain with the help of cryptocurrency prices. Peng et al. [19] utilized Generalized Autoregressive Conditional Heteroskedasticity (GARCH) together with Support Vector Regression so as to forecast prices of Bitcoin, Ethereum, and Dash and demonstrated significant improvement. Autoregressive Integrated Moving Average (ARIMA) has been one of the extensively used classical time-series analysis models. Later, Poongodi et al. [20] adopted linear regression and SVM based prediction model for Ethereum using time-series data. Sin and Wang [21] predicted bitcoin prices by the means of the ANN ensemble approach recognized as the Genetic Algorithm based Selective Neural Network

Ensemble (GASEN). Sentiment or how people perceive the currency is a very important factor in driving the prices of cryptocurrencies. Jain et al. [22] used tweets to perform sentiment analysis of cryptocurrency and incorporated them in prediction. Madanayake et al. [23] used tweets and historical data to forecast prices of Bitcoin, Ethereum, and Bitcoin Cash. Smuts [24] also used Telegram Sentiment data and Google Trends data for Bitcoin and Ethereum price prediction. Cheuque and Reutter [25] involved influencers historical prices and sentiments as inputs to RNN and sought to ameliorate the outcomes. Mittal et al. [26] attempted to devise a correlation between tweet volume, tweet sentiments, google search trends, and bitcoin prices. They came up with an outcome that three tweet sentiment analyses displayed the least accurate results. By utilizing daily generated data such as price, block size, a number of transactions per block, and other 26 features of the bitcoin blockchain together with twitter data, Mohanty et al. [27] tried to forecast fluctuations in bitcoin prices.

2.2 Summary of neural networks and deep learning

As a kind of artificial neural network, Recurrent Neural Networks (RNN) use sequential data or time series data and are notable by their memory because they achieve information from previous inputs to affect the existing input and output. Unlike traditional deep neural networks assuming inputs and outputs as independent, the outputs of recurrent neural networks are dependent on the previously existing elements inside the sequence. As well as, while future events could greatly contribute to determine a given sequence output, we cannot consider these events to predict unidirectional recurrent neural networks.

Artificial neural networks hold a multifaceted capacity and have been extensively applied to solve many problems [28]. To appease Bitcoins high exchange rate volatility, the most fitted machine learning techniques have come up with about 10% accuracy in its price predictions [29]. Ayodele et al. [30] concluded that the concept of neural networks is rooted in artificial intelligence. In other words, a neural network constitutes a series of algorithms endeavoring to specify underlying relationships within a dataset via a process imitating the human brains operating way. Considering this concept, neural networks correspond to a system of neurons that are either organic or artificial in nature. Being adaptable to changes in inputs, neural networks generate the fitted possible result, not requiring to redesign the criteria of output. Neural networks have proven themselves to be good at solving many tasks. They may have the most practical effect in the following three areas: modeling and forecasting, signal processing, and expert systems [31]. Neural networks convey a noticeable predictive ability in forecasting, whose auto associative memory part deals with predictive type problems. The technique that is utilized in neural network prediction is referred to generalization [32]. Generalization differs from auto associative memory, in a form that when the network is trained, the

network accepts a set of new data as input to forecast the output. Poria et al. [33] compared the application of neural network and multi-factor model in the field of quantitative investment.
From this standpoint, RNNs would confront two problems of exploding gradies and vanishing gradients. The gradients size, defined as the slope of the loss function in line with the error curve, plays a major role in emerging these issues. Once the gradient becomes too small, it keeps to be smaller, which continues to update the weight parameters until they become insignificanti.e., 0. By doing so, the algorithm stops learning. Exploding gradients takes place in larger gradients, which creates an unstable model. This case makes the model weights grow too large, which will be finally shown as NaN. To solve these problems, the number of hidden layers inside the neural network can be reduced, which eliminates partially the complexity in the RNN model.
Deep learning (DL) represents a state-of-the-art method of machine learning (ML) which is based on artificial neural network (NN) algorithms. Compared with traditional ML techniques like support vector machine (SVM) and k-nearest neighbors (kNN), DL is a promising branch of artificial intelligence and possesses strong points of the unsupervised feature learning, generalizations robust aptitude, and a strong training capacity for big data [7].
Deep learning is a format of neural network, which takes metadata as input and then processes the data through a number of layers to compute the output [34]. While conventional neural network can only manage single hidden layer (Fig. 1, right), deep learning processes the input data by a large number of hidden layers in its structure (Fig. 1, left). Each layer is made of nodes, which is the place for computation to occur. A node combines input from the data with a set of weights to determine whether to amplify or dampen the input, which in turn assigns significance to the inputs. These input-weight products are then summed and evaluated to decide to what extent the information propagates through the network to finally influence the classification. In a more holistic view, the hidden layer trains the unique set of features using the output of the previous layer. This process is known as nonlinear transformation. The more hidden layers it has, the more complex and abstract the data will become. In addition, the traditional neural network also requires more information about features for conducting the feature selection and feature engineering. By contrast, the deep learning neural network has no requirement for any information about features [35]. It performs as automatic feature extraction without any human intervention, grasping the relevant features necessary to solve the problem. In other words, deep learning performs optimum model tuning and selection on its own, which saves a lot of human effort and time.

Kucharcikova et al. [36] used deep learning technology to predict the stock price trend, which showed that the deep learning algorithm had a high abstraction ability in the stock price trend prediction problem, and could find the characteristic data

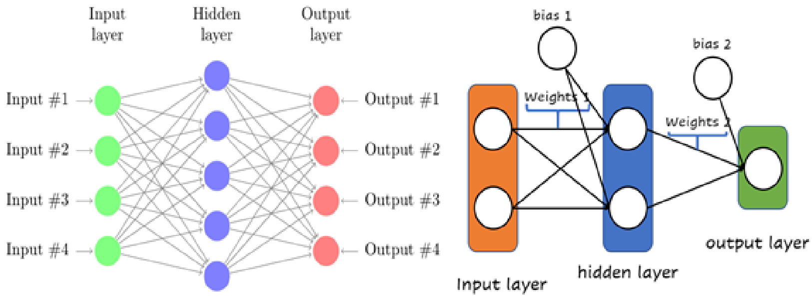

Figure 1: Neural network (right) and deep learning (left)

of the prepared response samples; they also use these results to make a good prediction. Pimentel et al. [37] employed deep learning and evolutionary computation to predict foreign exchange prices and optimize their portfolios. The results also indicate that this method can achieve profitability in foreign exchange transactions. Nine technical indicators were selected to predict the stock price. The prediction results of convolution neural network, artificial neural network and support vector machine model were compared. The results revealed that the convolution neural network generates better results and could be used as an ideal model to predict the stock situation. Application of deep learning to predict the value of stock data showed that the stock price predicted by this method was more accurate and had certain application value in stock income generation [38]. Naik and Mohan [39] used machine learning and deep learning technology to analyze the fluctuation of stock price, and took the Indian stock market as a case to study. The result showed that 33 technical indicators extracted from daily stock price were used to forecast the trend under machine learning and deep learning model, and the performance of deep learning model was better than that of machine learning technology. From the numerical point of view, the accuracy of classification was particularly remarkable. The classification accuracy could be improved by 5%-6% using deep learning model.

2.3 Disadvantage of RNN

Recurrent Neural Networks suffer from short-term memory. If a sequence becomes sufficiently long, RNNs will experience complexity in conveying data from preliminary time steps to upcoming ones. In addition, during back propagation, recurrent neural networks suffer from the vanishing gradient problem. Gradients are values used to update a neural networks weight. The vanishing gradient problem appears as the gradient shrinks by propagating backward through time. If a gradient value is too small, it stopes learning; this phenomenon is prevalent in the earlier layers. Therefore, RNNs would forget what it observes in longer sequences for layers that do not learn, that a short-term memory is assigned for them. LSTM s and GRUs have been developed as the solution to short-term memory, possessing internal mechanisms which are called gates regulating information flow.

2.4 Long short-term memory (LSTM)

Long short-term memory (LSTM) neural networks (shown in 2) have been developed by recurrent neural networks (RNN), lacking long-term dependence problems because their storage unit structure is unique, while helping predict financial time series [**?**]. LSTM networks are recognized as a very helpful method in learning and predicting temporal data, particularly economical and financial data with long term dependencies. Belonging to the class of recurrent neural networks (RNNs), short-term memory networks (LSTMs) are one of the most sophisticated deep learning architectures, first introduced by Sepp Hochreiter and Jurgen Schmid Huber in 1997, and widely used to date with many variants derived. Specifically designed to learn long-term dependencies, LSTM networks enable overcoming RNNs previously inherent problems like vanishing and exploding gradients [40]. In comparison with ordinary RNN, LSTM adds input gate and forget gate to solve the problem of gradient disappearance and gradient explosion, so that long-term information can be captured, and it can have better performance in long sequence text. The input and output structure of GRU is the same as ordinary RNN, but its internal structure is similar to LSTM [41]. In an age when computing power is no longer a bottleneck, LSTM is actually more suitable in these scenarios. Yang et al. [42] adopted an LSTM model to forecast the bitcoin prices. Tandon et al. [43] used LSTM along with ten-fold cross-validation for prediction of bitcoin prices. Abu Hashish et al. [44] proposed a hybrid model using hidden Markov models and LSTM and improved results over traditional ARIMA and LSTM. Yiying and Yeze [45] analyzed the price dynamics of Bitcoin, Ethereum, and Ripple using ANN and LSTM.

The functions of LSTM are in 1 as follows:

$$\begin{aligned} f_t &= \sigma(w_f.[h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(w_{i^2}.[h_{t-1}, x_t] + b_i) \\ O_t &= \sigma(w_0.[h_{t-1}, x_t] + b_0) \\ C_t &= tanh(w_c.[h_{t-1}, x_t] + b_c) \\ g_t &= tanh(x_t U^g + h_{t-1} W^g) \\ h_t &= tanh(c_t).0 \end{aligned} \tag{1}$$

Where, f_t, i_t, c_t and O_t represent vectors for the respective gates activation values. w_f, w_i, W_0, W_c are weight metrics. b_f, b_i, b_0, and b_c bias vectors. x_t shows the input vector at timestep t. h_t poses a vector for the LSTM layers output. σ represents a sigmoid function.

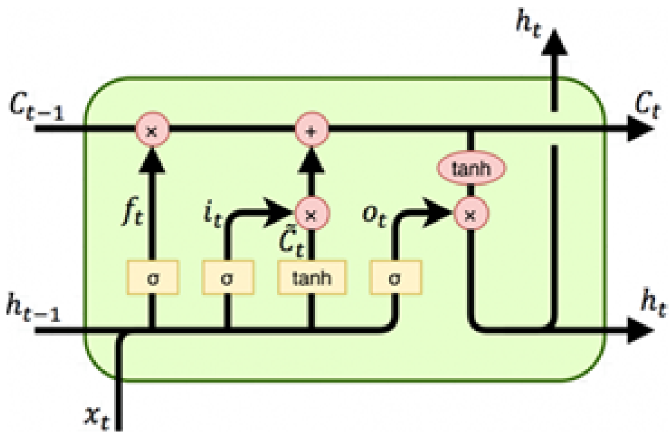

Figure 2: LSTM structure in the house [10]

2.5 Gated recurrent unit (GRU)

Gated recurrent units are a new generation of recursive networks and very similar to Long short-term memory networks. Unlike short-term memory networks, these networks do not have an input / output port, leaving this to the hidden area of the repeating port cell. Duplicate port cells have only two units, one restart unit and other update unit. In these cells, the update unit acts as the input port and output port of the long short-term memory cells, and it is responsible for deciding what data to add or remove. The open unit is the beginning of the unit, which decides what information from the past to forget. The structure of Gated recurrent unit cell is shown in 3. The functions of an iterative port cell are as equation 2 as

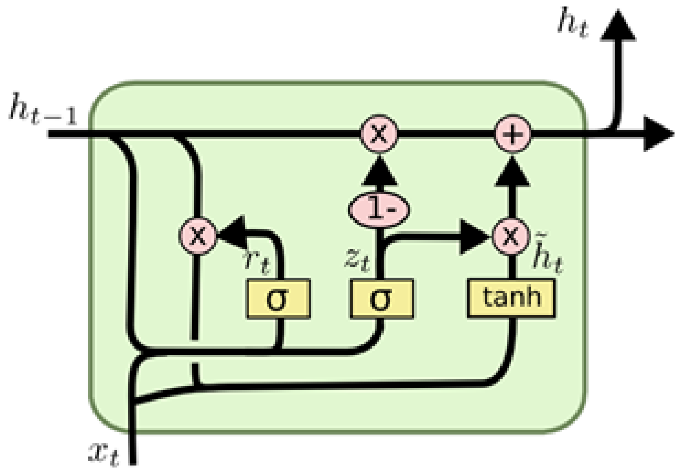

Figure 3: Gated recurrent unit cell structure [10]

follows:

$$
\begin{aligned}
r_t &= \sigma(w_r.[h_{t-1}, x_t] + b_r) \\
Z_t &= \sigma(w_Z.[h_{t-1}, x_t] + b_Z) \\
K_t &= tanh(x_t U^k + h_t - 1.r)W^k) \\
h_t &= (1 - z).k + zh_{t-1}
\end{aligned} \tag{2}
$$

Where, r_t is the reset gate factor, x_t is input factor, h_t is output factor, Z_t is update gate vector, W, U and b are parameter matrices and vector, respectively. σ also represents a sigmoid function.

The similarities and differences between these two systems are as follows: LSTM and GRU are very popular in terms of sequencing in deep learning. With superior operating capabilities relative to each other, the GRU structure is simpler and requires less computing power, so it can be used to form very deep networks. However, LSTMs have more power because they have more gates, but they need a lot of computing power. GRU can save a lot of time without compromising performance. However, through empirical research, this advantage of GRU is only in the scenario of long text and small datasets. In other scenarios, the GRU performance decline is more severe than in LSTM. In an age when computing power is no longer tight, LSTM is more appropriate in these scenarios.

3 Methodology

Price forecasting model has three stages: data collection and preprocessing, model establishment and training, and evaluation of experimental results. The current paper duplicated this three-stage process for LSTM and GRU.

3.1 Dataset Description

In order to obtain optimal performance in Long short-term memory and Gated recurrent unit model, we should use long-term data in models. Therefore, our study cryptocurrencies' data containing Open, High, Low, Close, Volume, sourced from yahoo finance, ranges 27th April 2015 till 27th April 2021 for bitcoin, Litecoin, ripple, and from 27th August 2015 till 27th April 2021 for Ethereum. The opening price (open) is the first transaction price of a cryptocurrency for a day, the closing price (close) poses its final price for that day, High is the highest price of a given cryptocurrency at the same trading day, low is the lowest price of that day and Volume refers to the number of transactions in a time unit. Average analysis statistics of selected cryptocurrencies are listed in table 1 and brief statistics (Tables 1 to 5) and plot of OHLCV (in USD) vs. time can be seen in Figures 4 to 7.

Table 1: Average analysis statistics of BTC, ETH, LTC, Ripple

Cryptocurrency	Min	Max	Standard deviation	Mean
Bitcoin	210.495	63503.46	10932.43	7701.675
Ethereum	0.4348	2634.3	419.92	309.05
Litecoin	1.36	358.34	61.72	58.14
Ripple	0.00409	3.3778	0.3344	0.2737

Table 2: Bitcoin brief statistics

Data	Open	High	Low	Close	Volume
27-Apr-2015	219.429	233.305	218.023	229.286	38574000
28-Apr-2015	228.969	229.495	223.069	225.855	21469200
29-Apr-2015	225.591	229.495	223.069	225.855	21469200
				.	
25-Apr-2021	50052.83	50506.02	47159.48	49004.25	4.61E+10
26-Apr-2021	49077.79	54288	48852.8	54021.75	5.83E+10
27-Apr-2021	54149.23	55172.7	53319.19	54953.15	5.06E+10

Figure 4: Bitcoin plot of OHLCV (in USD) vs. time

Table 3: ETH brief statistics

Data	Open	High	Low	Close	Volume
27-Aug-2015	1.16981	1.18883	1.13729	1.1477	686662
28- Aug-2015	1.14766	1.20779	1.1205	1.19138	721872
29- Aug-2015	1.19353	1.20721	1.14949	1.18255	375377
				.	
25-Apr-2021	2214.414	2354.087	2172.515	2316.06	3.18E+10
26-Apr-2021	49077.79	2536.337	2308.315	2534.482	3.52E+10
27-Apr-2021	2546.232	2665.629	2487.371	2634.302	3.25E+10

3.2 Software and hardware

Python 3.8 pyxis [1] was used for all data processing and analysis, utilizing the packages pandas [[47], [48], [49], [2]]. We use the koras library provided by [51] on top of the tensor flow backend [52] to build our deep learning, LSTM, and GRU networks, and import dense and drop out. Moreover, we make use of sci-kit learn by [53] to select feature with random forest based on [54] models and min max scaler to normalizing and mean squared error to calculate error for the standard

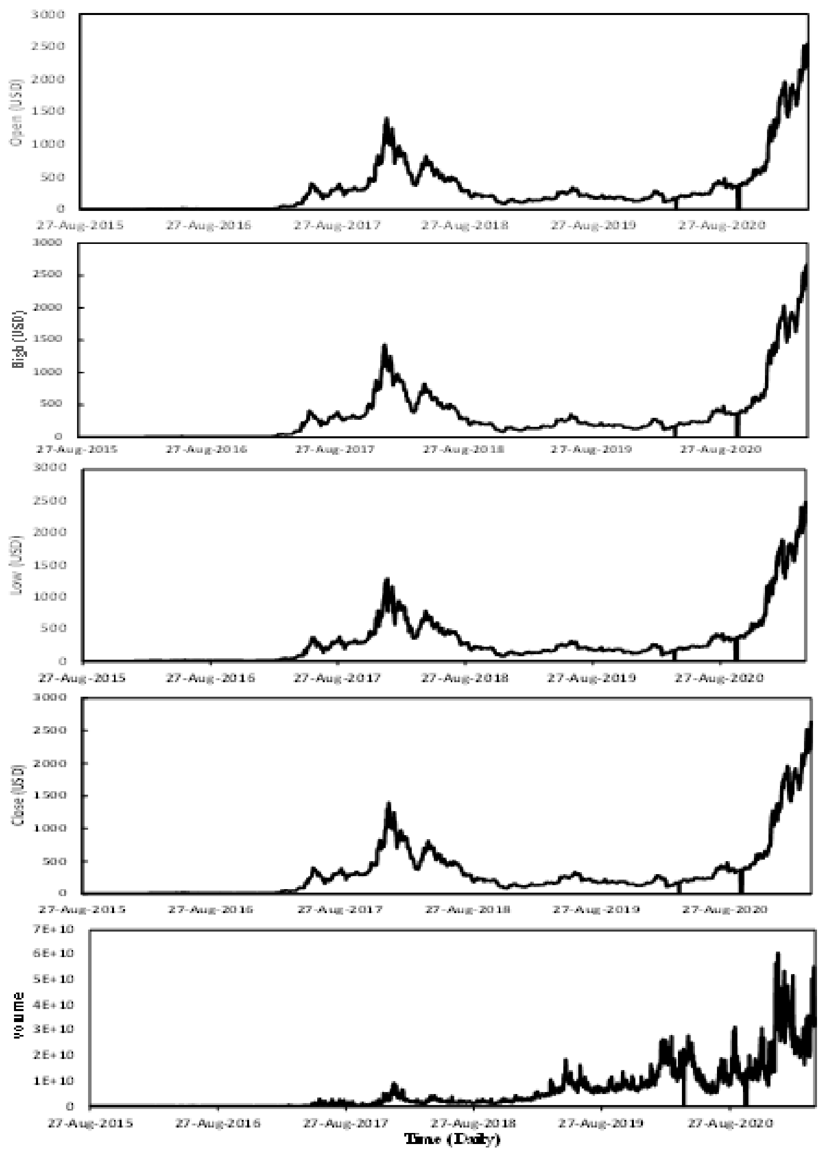

Figure 5: ETH plot of OHLCV (in USD) vs. time

deep net. The LSTM network is trained on NVIDIA GPUs, while all other models are trained on a CPU cluster. All neural networks and others utilize the GPU-based Nvidia CUDA parallel computing platform (GeForce GTX 1080), while the random forest and logistic regression models are trained on CPU (Intel Core i7-6820 HQ, 3.60 GHz).

Table 4: LTC brief statistics

Data	Open	High	Low	Close	Volume
27-Apr-2015	1.32185	1.39635	1.32185	1.38348	1465060
28- Apr -2015	1.38264	1.38634	1.35215	1.36402	1014190
29- Apr -2015	1.36257	1.36815	1.34949	1.36132	1372440
				.	
25-Apr-2021	224.9218	235.2061	212.2868	223.6329	3.7E+09
26-Apr-2021	223.9871	247.9587	221.9104	247.4059	4.94E+09
27-Apr-2021	249.1273	262.424	244.109	261.9395	4.7E+09

Table 5: Ripple brief statistics

Data	Open	High	Low	Close	Volume
27-Apr-2015	0.007742	0.007846	0.007675	0.007765	779357
28- Apr -2015	0.007764	0.007764	0.007607	0.00763	569295
29- Apr -2015	0.007633	0.007863	0.00763	0.00763	549981
				.	
25-Apr-2021	1.04949	1.153025	0.952915	1.032256	8.57E+09
26-Apr-2021	1.035183	1.369077	1.016921	1.368506	1.54E+10
27-Apr-2021	1.385799	1.458148	1.336754	1.408819	1.43E+10

3.3 Input variables

Choosing the right input variable among other variables has always been a challenge for researchers. Technical indicators and price lags have appeared to be suitable option to effectively explain and reflect market conditions. In this study, according to the literature on the previous subject, we use technical indicators and t+10th days price lags and OHLCV as variable. Extracted daily data is added to different technical indicators which use them to individualize between a noisy temporary price spike from a long-term trend reversal, meant that our model identifies a genuine price trend from a market anomaly. Indicators can be divided into four fundamental kinds: volume, trend, momentum and volatility indicators [55].
Volume indicators like MFI , use the trading volume to determine the strength of a continuing trend. Momentum indicators like RSI and Stochastic Indicators find out the rate of change of price in a given period of time and represent the health of a current rally. Trend Indicators such as MACD are adopted to pick up only just any developing trend reversals within the markets. Volatility indicators like ADX have been used to measure the strength of trend based on the highs and lows of the price bars over specified numbers of bars. The list of indicators and lags used in this article is specified in Table 6.

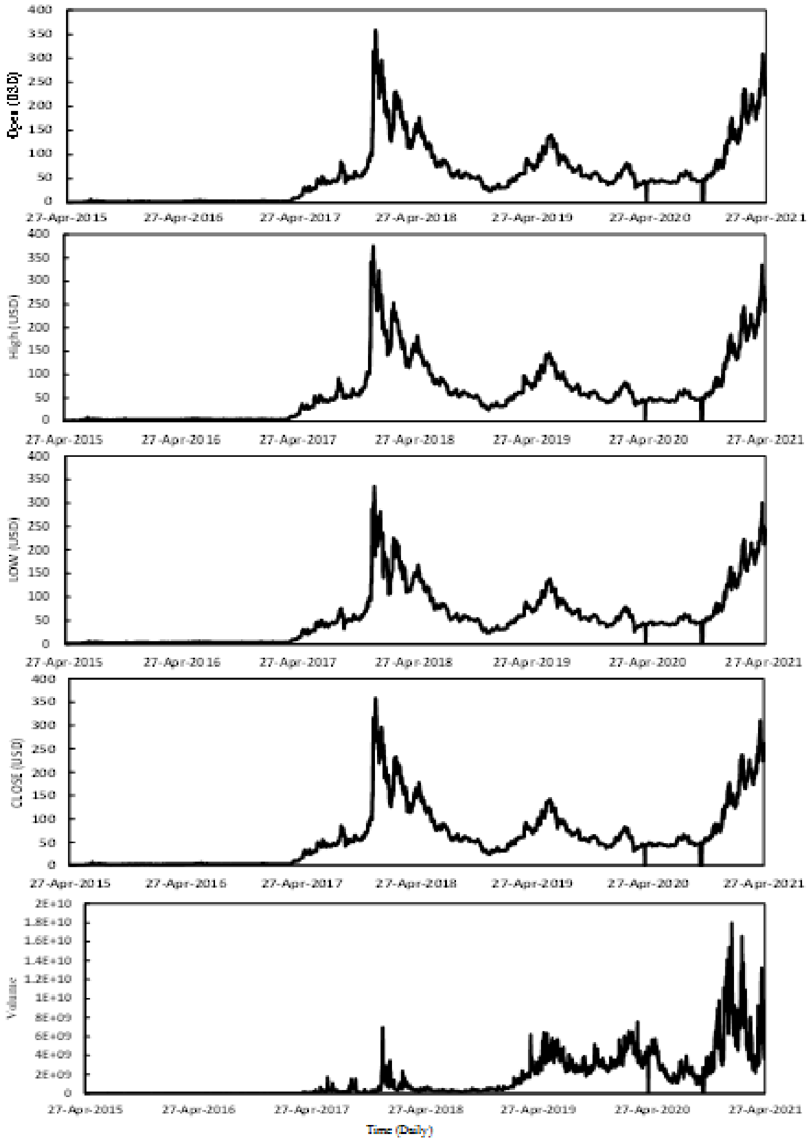

Figure 6: LTC plot of OHLCV (in USD) vs. time

The process of identifying only the most relevant features to the dependent variable is called feature selection. Feature selection methods comes up with a method that reduces computation time, improves prediction performance, and provides a better understanding of the data in machine learning or pattern recognition applications [56]. In this paper, we use the random forest technique based on the essence of feature selection (Table 7). Random forest is one of the most popular and widely

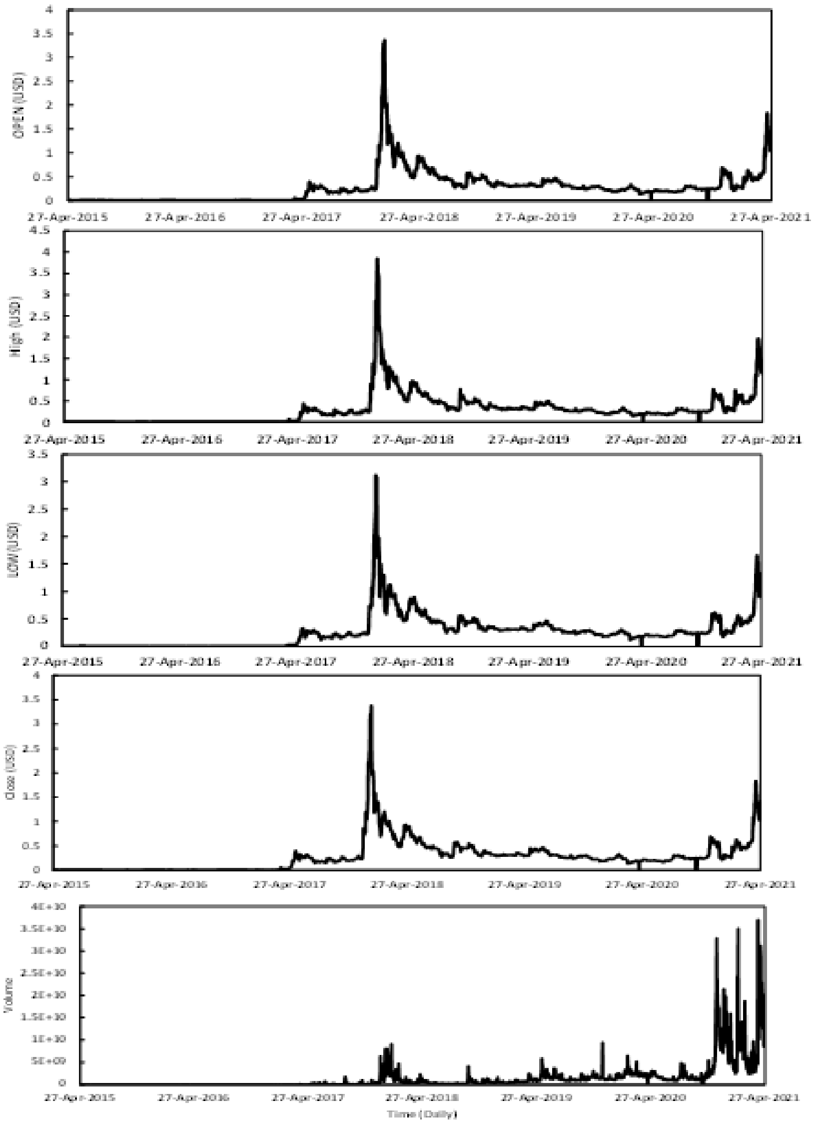

Figure 7: Ripple plot of OHLCV (in USD) vs. time

used algorithms among machine learning techniques. The reason for the success of this algorithm pertains to its high predictive power, the less possibility of overfitting and their convenient understanding.

This algorithm is easily perceivable because the importance of each variable can be readily extracted using the decision tree. Each decision tree does not have the ability to access all observations or all independent variables, and this guarantees lack of correlation between the trees, and thus guarantees the fact the algorithm for selecting the explanatory variables is not over-fitted. Each decision tree used consists of a sequence of yes or no questions from one variable or a combination of several variables. After answering each question, the decision tree divides the data into two clusters, each cluster is the place of collection of observations with the most similarity and with the greatest difference compared to the opposite cluster. As a result, the selected independent variables to enter the studied algorithms are chosen from the clusters that have the highest percentage of similarity and in this paper 25 variables are selected out of 43 variables as feature, showing the highest percentage of explanation; from these 25 variables, 24 of them are chosen as feature (independent variable) and one as dependent variable.

Table 6: Overview of indicators and other variables incorporated for feature selection in this research

Raw	Indicator	Variables involved in the indicator
1	Average Directional Movement Index	High Low Close
2	Average Directional Movement Index Rating	High Low Close
3	Absolute Price Oscillator	Close
4	Aroon	High Low
5	Aroon Oscillator	High Low
6	Balance Of Power	OpenHightLowClose
7	Commodity Channel Index	High Low Close
8	Chande Momentum Oscillator	Close
9	Directional Movement Index	High Low Close
10	Moving Average Convergence/Divergence	Close
11	Money Flow Index	High Low Close Volume
12	Minus Directional Indicator	High Low Close
13	Minus Directional Movement	High Low
14	Momentum	Close
15	Plus, Directional Indicator	High Low Close
16	Plus, Directional Movement	High Low
17	Percentage Price Oscillator	Close
18	Rate of change	Close
19	Rate of change Percentage	Close
20	Rate of change ratio	Close
21	Rate of change ratio 100 scale	Close
22	Relative Strength Index	Close
23	Stochastic	High Low Close
24	Stochastic Fast	High Low Close
25	Stochastic Relative Strength Index	Close
26	1-day Rate-Of-Change (ROC) of a Triple Smooth EMA	Close
27	Ultimate Oscillator	High Low Close
28	Williams'R	High Low -Close
29	First lag Close price(target)	Close
30	Second lag Close price(target)	Close
31	Third lag close price(target)	Close
32	Fourth lag close price(target)	Close
33	Fifth lag close price(target)	Close
34	Sixth lag Close price(target)	Close
35	seventh lag Close price(target)	Close
36	eighth lag Close price(target)	Close
37	ninth lag Close price(target)	Close
38	tenth lag Close price(target)	Close
39	open	-
40	high	-
41	low	-
42	close	-
43	Volume	-

Table 7: List of input variable by feature selection using random forest

Raw	Indicator	Variables involved in the indicator
1	Average Directional Movement Index	High Low Close
2	Average Directional Movement Index Rating	High Low Close
3	Absolute Price Oscillator	Close
4	Balance Of Power	Open Hight Low Close
5	Commodity Channel Index	High Low Close
6	Chande Momentum Oscillator	Close
7	Directional Movement Index	High Low Close
8	Moving Average Convergence/Divergence	Close
9	Money Flow Index	High Low Close Volume
10	Minus Directional Indicator	High Low Close
11	Minus Directional Movement	High Low
12	Momentum	Close
13	Plus, Directional Indicator	High Low Close
14	Plus, Directional Movement	High Low
15	Percentage Price Oscillator	Close
16	Rate of change ratio 100 scale	Close
17	Relative Strength Index	Close
18	Stochastic	High Low Close
19	Stochastic Fast	High Low Close
20-21	Stochastic Relative Strength Index	Close
22	1-day Rate-Of-Change (ROC) of a Triple Smooth EMA	Close
23	Ultimate Oscillator	High Low Close
24	Williams'R	High Low -Close
25	close	-

3.4 Data Pre-processing

The dataset attributes contain varying range of values, that we use Min-max normalization data to scale values between a range of 0 to 1. Min-max normalization is one of the most common ways to normalize data. For every feature, the minimum value of that feature gets transformed into a 0, the maximum value takes 1, and every other value gets transformed into a decimal between 0 and 1. Min-max normalization guarantees all features and will have the exact same scale but is unable to handle outliers well. Score for each attribute in each record is calculated by the below 3:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

3.5 Data divided into training and test data

In this paper we use 6-year daily time series. In order to calculate indicator values, 88 datasets from the beginning are not available or missed, hence we eliminate that part from our data. In fact, our new range of data for BTC, LTC, XRP starts from 24th July 2015 to 27th April 2021, and for ETH from 23th November 2015 to 27th April 2021. Then, we divided data into training and test data with 9 to 1 corporation. We use the first nine-tenths of the data (approximately 63 months) to generate a training set; it means that the training data ranges between 24th July 2015 to 27th September 2020 and has 1890 records. The remaining one-tenth of data (approximately 7 months) is used to test our models and obtain a representative out-of-sample prediction. On the other hand, the testing set contains records from 27th September 2020 to 27th April 2021 and has 211 records. For ETH the training data ranges between 27th November 2015 to 11th October 2020 and has 1781 records. The remaining one-tenth of data (approximately 6 months and 18 days) is used to test our models and acquire a representative out-of-sample prediction. As a matter of fact, the testing set contains records from 11th October 2020 to 27th April 2021 and has 198 records.

3.6 Model establishment and training

The main goal of this paper is to compare the performance of LSTM with GRU approaches along the ability of forecasting price. In order to reach this goal, we adopted the same architecture in similar cryptocurrencies for both models and the specified topology of our trained LSTM, GRU network is hence as follows:
For Bitcoin
1- Input layer: Input layer with 24 features.
2- LSTM layers: LSTM networks hidden layers consist of 3 hidden layers. The first LSTM layer has 30 neurons and a dropout value of 0.1. The layer is again followed by an LSTM layer having 120 neurons and a dropout value of 0.05. The layer is again followed by an LSTM layer having 20 neurons and a dropout value of 0.1. In fact, each LSTM layer is followed by a dropout layer to avoid an over-fitting problem.
3- Output layer (dense layer): the output from networks is passed through a dense layer, which gives the final predicted price.
For ETH, LTC, XRP
4- Input layer: Input layer with 24 features.
5- LSTM layers: LSTM networks hidden layers consist of 3 hidden layers. The first LSTM layer has 40 neurons and a dropout value of 0.1. The layer is again followed by an LSTM layer having 140 neurons and a dropout value of 0.05. The layer is accordingly followed by an LSTM layer having 20 neurons and a dropout value of 0.1. In reality, each LSTM layer is followed by a dropout layer to avoid an over-fitting problem.
6- Output layer (dense layer): the output from networks is passed through a dense layer, resulting in the final predicted price. The main activation function used is ReLU and recurrent activation function is sigmoid. The optimizer is Adam, learning rate is 0.0005623 and decay is 0.007. Additionally, the model has been trained for 1000 epochs. Architecture of the GRU network is the same as LSTM (Fig. 8)

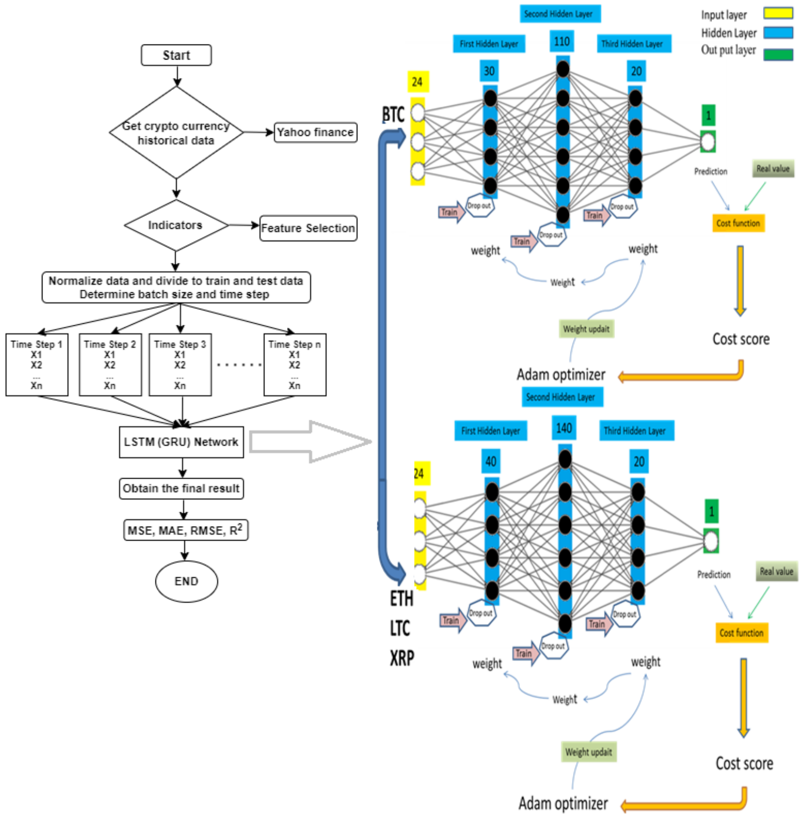

Figure 8: Architecture of BTC, ETH, LTC and XRP in LSTM-like GRU network

4 Experimental results

4.1 Evaluation Metrics

We evaluated the prediction results and established prediction model by the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R-squared) using equation 4. The smaller the MSE, RMSE, and MAE, the closer the predicted value to the true value; the closer the coefficient R-squared to 1, the better the fit of the model (Table 8):

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|y_i - Y_1|$$
$$MSE = \frac{1}{N}\sum_{n=1}^{N}(y_i - Y_2)^2 \tag{4}$$
$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_i - Y)^2}$$

where $Y1$ represents the predicted price, y_i represents the actual price, $Y2$ denotes the mean value, and N is total number of observations or sample.

Table 8: Results of evaluation metrics for cryptocurrencies BTC, LTC, XRP, ETH

Crypto	Analysis method	MAE	MSE	RMSE	R-2 score
BTC	LSTM	0.89	0.41088	0.641	0.7256
BTC	GRU	0.96	0.5155	0.718	0.6652
ETH	LSTM	0.24	0.09823	0.3134	0.58213
ETH	GRU	0.25	0.09974	0.3158	0.525266
LTC	LSTM	0.01207	0.0004481	0.02117	0.9391
LTC	GRU	0.0101	0.00033	0.01816	0.9501
XRP	LSTM	0.0123	0.00018	0.0134	0.9326
XRP	GRU	0.0121	0.00012	0.0109	0.9461

5 Results

We processed four cryptocurrencies data sets in the LSTM and GRU neural network model, trained them and compared the predicted results of each model in order to determine whether these differences in predictive accuracy with these two models are significant. Figures 9 to 12 demonstrate comparison results derived from LSTM and GRU models.

Figure 9: Bitcoin GRU vs. LSTM fit plot

Diebold Mariano test was used for predictive purposes. Table 9 shows the results of the Diebold Mariano test. The results indicate that forecasting differences between LSTM and GRU for bitcoin and Ethereum were significant and non-zero. And, LSTM reaches better accuracy than GRU but forecasting differences for XRP

Figure 10: ETH GRU vs. LSTM fit plot

Figure 11: LTC GRU vs. LSTM fit plot

Figure 12: XRP GRU vs. LSTM fit plot

and LTC were insignificant and zero, implying that both models approximately have same accuracy and we cannot prefer one of them.

Table 9: Diebold Mariano test results

DM test	BTC-USD	ETH-USD	LTC-USD	XRP-USD
D-M statistics	-14.8404	-16.2412	1.125234	1.063224
p-value	1.44E-29	5.39E-44	0.085331	0.102356

6 Discussion

In recent years, due to many developments which occur in the field of artificial intelligence, machine learning, and data mining, researchers have been able to extract information from data in a very different way which none of the classic statistical models such as, ARFIMA, FARIMA, ARCH and GARCH cannot do like them because of assumptions-induced limitations; coupled with, we know that Cryptocurrency price prediction has been a very challenging task for researchers due to the external or exogenous social and psychological factors that affect its price prediction. Many variants of neural networks are existing to analyze cryptocurrency prices. Among all, LSTM has been proved to be the best until now [1]. In current study, we established a forecasting framework to predict the prices of cryptocurrencies (BTC, ETH, LTC, XRP) and processed cryptocurrency data through LSTM neural network and GRU networks, in order to compare the accuracy of each model in predicting the price of cryptocurrencies. The experimental results of comparing LSTM and GRU uncovered that our proposed model LSTM has a better fitting degree and improved prediction accuracy for Bitcoin and Ethereum, complying with the results found by [14], [55]. As well as, the research study demonstrated that GRU shows better accuracy than LSTM for Litecoin and Ripple, that are in consistent with findings by researchers [57], [12].

7 Conclusions and Future Research

Predicting price is one of the major issues in financial market and researchers encounter numerous challenges in this field. Almost, all traders believe that cryptocurrency market is the most volatile market, that predicting price in such financial environment has become one of the most complicated fields among financial instruments. A brief description of challenges in the domain of cryptocurrency price prediction, mentioned in a Deep Learning-based Cryptocurrency Price Prediction Scheme for Financial Institutions article by [1], are as follows: 1) Vast availability of different cryptocurrencies, 2) High volatility of cryptocurrency prices, 3) Technological innovations, 4) Public perception and acceptance, and 5) Legal aspects and issues. The current study found that an attention-based LSTM method predicts higher accuracy price time series in cryptocurrency than GRU. However, we employed indicators as features in our model, in order to increase the accuracy. One of the most significant matter in cryptocurrency market, which can be considered in the future modeling to increase the accuracy, is to include the influence and importance of tweets and associated news in cryptocurrency market.

Declaration of competing interest

The authors proclaim that there are no competing financial interests or personal relationships that could influence the work presented in this paper.

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