# Predicting Cryptocurrency Price Returns by Using Deep Learning Model of Technical Analysis Indicators

**Negar Fazlollahi and Saeed Ebrahimijam**

**Abstract** Over the last few years, cryptocurrencies have become a new alternative exchange currency for the global economy. Due to the high volatility in the prices of cryptocurrencies, forecasting the price movements is considered a very complicated challenge in the world of finance. Technical analysis indicators are one of the prediction tools which are widely used by analysts. These indicators, which are explored from the historical prices and volumes, might have useful information on price dynamics in the market. Meanwhile, with the new advances in artificial intelligence techniques, like long short-term memory (LSTM), which is able to keep the track of long-term dependencies; there is the extensive application of deep neural networks for predicting nonstationary and nonlinear time series. This study provides a forecasting method for cryptocurrencies by applying an LSTM multi-input neural network to investigate the prediction power of the lags of technical analysis indicators as the inputs to forecast the price returns of the three cryptocurrencies; Bitcoin(BTC), Ethereum (ETH), and Ripple (XRP) that have the highest market capitalization. The results illustrate that the proposed method helps the investors to make more reliable decisions by significantly improving the prediction accuracy against the random walk over the maximum trading time of BTC, ETH, and XRP datasets.

**Keywords** Cryptocurrency · Deep learning model · Random walk

## Introduction

The fast pace of growth in information technology has considerably influenced many sectors; including finance, making the digitalization of financial products and processes more common. Nowadays, cryptocurrencies, as one of the digitalizations

N. Fazlollahi (✉) · S. Ebrahimijam
Department of Banking and Finance, Eastern Mediterranean University, Famagusta, North Cyprus via Mersin 10, Turkey
e-mail: negar.fazlollahi@emu.edu.tr



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in finance, are quite widespread. (Dwyer, 2015). These currencies are a new electronic alternative exchange currency method that owns online transactions and is designed based on digital cryptography algorithms. (Ferdiansyah et al., 2019).

Currently, trading in cryptocurrencies is quite predominant, owning the market similar to the stock market. However, due to its high volatility, there is a need for a forecasting method for investors to help them make better decisions in their trading investments (Radityo et al., 2017).

Bitcoin, which was developed in 2009, is the most prominent digital currency today. Each bitcoin has an address and a transaction takes place by trading the bitcoins from one address to another. (Dwyer, 2015). This record is called the "block chain," which is the chain of records of transactions in the form of blocks with each of the blocks having its specific key. A block encompasses cryptographically encoded data locked by its key and the data of the prior block, the entire chain of blocks is created in this regard (Tanwar et al., 2021).

Many cryptocurrencies made their appearance in the crypto market after Bitcoin; Ethereum, and Ripple are among them that draw the attention of many investors. Ethereum developed in 2015, with a market capitalization of $410 billion, and became the second largest cryptocurrency (Tanwar et al., 2021).

In general, cryptocurrency trade is considered one of the most outstanding kinds of profitable investments which comes with its pros and cons. The distinctive characteristic of cryptocurrency is fluctuations in price and high volatility on a regular basis. This characteristic makes their forecasting of them quite challenging.

Nowadays, a different variation of Artificial Neural Network is used to compute the crypto market prediction. In this study, we applied one of the new advances in artificial intelligence techniques, called Long Short Term Memory (LSTM), which is capable of tracking long-run dependencies, and also has the extensive application of deep neural systems to forecast nonstationary and nonlinear time series.

Besides, the study gets the help of technical analysis indicators, which are remarkable forecasting tools. These indicators, through exploring the historical prices and volumes, deliver useful insight and information on price dynamics in the market. More specifically, we incorporate four technical analysis indicators. The adoption of technical analysis is a great concern for both individual and institutional investors, as well as portfolio managers in asset allocation and risk management (Ma et al., 2020).

The objective of this research is to examine a forecasting method for cryptocurrencies by applying the LSTM multi-input neural network to investigate the prediction power of the lags of technical analysis indicators as the inputs to predict the price returns of the three cryptocurrencies, Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP), that have the highest market capitalization. In other words, in this work, we investigate the prediction power of the changes of the lags of technical analysis indicators as the inputs to project the price returns of the mentioned cryptocurrencies, by applying the LSTM multi-input neural network method.

The remainder of the study is structured in this way: in the second part, we present a review of the literature. The data and methodology are illustrated in the third and fourth parts. Empirical results are discussed in part five. And section six drives the conclusion.

## Literature Review

There are enormous previous studies that applied technical analysis indicators to predict stock price movements and directions. Among them, de Souza et al. (2018) use technical analysis of the stock price movements of BRICS countries. And Chen et al. (2018) created a new technical analysis dynamic that helps investors decide on a more profitable way. Also, Kuang et al. (2014) examine the technical analysis of profitability in the emerging foreign exchange market of ten countries. In this study, we use four technical analysis indicators as input to our model.

Regarding the usage of deep learning methods for forecasting cryptocurrency price and directional movements, there are various valuable previous works that, in this section, we will briefly present here.

Derbentsev et al. (2020) explored different short-term forecasting models (binary autoregressive tree [BART], random forecast [RF], multilayer perceptron [MLP]) for cryptocurrency prices. They examined Bitcoin, Ethereum, and Ripple (due to their high market capitalization) from August 2015 to December 2019 with 1583 observations. Their outcomes exhibited that BART and MLP models have 63% efficiency in forecasting directional movements, which were higher than the "naive" model.

Livieris et al. (2020) combined three joint learning approaches – ensemble-averaging, bagging, and stacking – alongside the advanced deep learning methods for forecasting cryptocurrency prices of Bitcoin, Ethereum, and Ripple from January 2018 to August 2019. Their results illustrated that their model can be reliable and strong in forecasting.

Patel et al. (2020) applied GRU-based hybrid and LSTM for predicting cryptocurrency prices of Litecoin and Monero from January 2015 to February 2019; they incorporated the average, open, and close prices, also high and low prices as well as trading volume. The result of their study explicated that their model outperforms the traditional LSTM model.

Li et al. (2019) used the multiple input LSTM-based forecasting model and the Black-Scholes (BS) method to predict the prices of bitcoin. They concluded that Blockchain statistics significantly impact their proposed forecasting model.

Wu et al. (2018) applied two LSTM models (conventional LSTM and LSTM with AR[2]) to predict the daily prices of Bitcoin from January to July 2018. Their results explicated the best forecasting accuracy of the proposed model with AR(2).

Most of the previous research applied complex models and methods to attain a better prediction of the price of the cryptocurrency. In this research, we propose a different approach for the development of reliable forecasting; we use the technical analysis indicators as inputs to our model and employ training data with a special architectural design. Notably, we propose an LSTM multi-input neural network model, with the changes in the lag of four technical analysis indicators as inputs exploring the past 14 days of data, in order to predict the direction of next-day prices of cryptocurrencies. As far as we reviewed previous literature, this is the first study that brought focus on the technical analysis as input to exhibit a more accurate prediction of cryptocurrencies.

# Data

## *Price Returns*

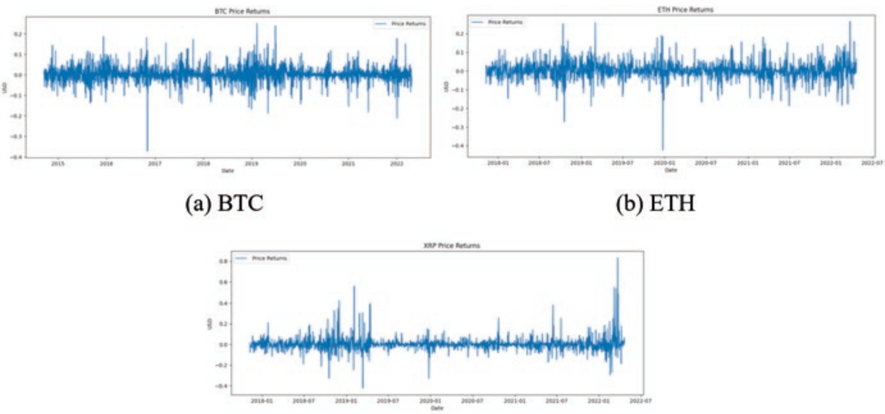
The collected data is the daily close prices of Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) from the yahoo finance database. The objective behind selecting these cryptocurrencies among others is that they possess the highest market capitalization. BTC data covered the period of 2014 to 2022 with 2778 observations. ETH data comprised the period of 2017 to 2022, having 1626 observations. And XPR data encompassed the period of 2017 to 2022, owning 1626 observations. We then convert the prices into returns. The study incorporates all of the available data.

$$\text{Price return} = \frac{Closing\ price_t \ - Closing\ price_{t-1}}{Closing\ price_{t-1.}}$$

where closing price is the final share price at the end of the daily trading, t is time as of today, and $t - 1$ is yesterday

The below graphs illustrate the price returns of bitcoin, Ethereum, and ripple (Fig. 1).

The data used as the input to our model is the changes in the lags of four technical analysis indicators in order to predict the next day's cryptocurrency price returns.




(a) BTC (b) ETH

(c) XRP

**Fig. 1** Price returns of BTC, ETH, XRP

## Technical Analysis Indicators

Technical analysis indicators use the price and volume of the shares; they are not based on the profit and earnings of the firm, rather they predict future price patterns by previous historical prices and trends. These indicators serve as the prediction of short-term price movement for active stock traders and benefit long-term investors to predict buy and sell periods.

In this research, regarding the independent variables, the various lags of four technical analysis indicators are used in our structural regression model. These indicators measure the velocity and the magnitude of directional price changes, buyer's enthusiasm trend, the tendency of a closing price compared to the high and low price range, and demand and supply volumes. (Brock & De Lima, 1996; Pathirawasam, 2011) (Table 1).

RSI (Relative Strength Indicator) is used as a criterion for measuring the velocity and the magnitude of directional price changes (Wilder, 1978) (see Eq. [1]). In Eq. (1) $\overline{\Delta P_i^+}$ and $\overline{\Delta P_i^-}$ are average positive (+) and negative (−) price change, respectively, during the last $n$ minutes ago. According to Wilder (1978), the best-assigned $n$ is 14.

$$RSI(n) = 100 - \frac{100}{1 + \frac{\sum_{i=1}^{n} \overline{\Delta P_i^+}}{\sum_{i=1}^{n} \overline{\Delta P_i^-}}} \tag{1}$$

MFI (money flow indicator) refers to the forecasting reliability of the buyer's enthusiasm trend. It is an indicator of money flowing "into" or "out of" an asset; however, the expression only refers to the forecasting reliability of the buyer enthusiasm trend (see Eqs. [2] and [3]). Obviously, there is never any net money in or out; for every buyer, there is a seller of the same amount (Kirkpatrick II & Dahlquist, 2010).

$$MFI_t = 100 - \frac{100}{1 + \frac{Positive money\ flow_t}{Negative money\ flow_t}} \tag{2}$$

$$Money\ flow_t = \frac{price_t^{high} + price_t^{low} + price_t^{close}}{3} \times volume_t \tag{3}$$

**Table 1** List of four technical indicators

| RSI | MFI | STOCH | OBV |
|---|---|---|---|

STOCH (Stochastic Indicator) investigates the tendency of changes in the closing price in comparison to the high and low price variety throughout a particular span (Lane, 2007) (see Eq. [4]).

$$\text{STOCH} = \frac{Pricecloselast - Pricelowest}{Price\,Highest - Price\,Lowest} \times 100 \tag{4}$$

OBV (on balanced volume) OBV measures demand and supply volumes by assessing the trading volumes ($V_t$). The change in OBV is considered a factor in the decision-making process by market analysts (Granville, 1976) (see Eq. [5]). It shows the movement of volume resulting from the closing price ( $price_t^{close}$ ) changes (Blume et al., 1994).

$$OBV_t = OBV_{t-1} + \begin{cases} V_t & if \quad price_t^{close} > price_{t-1}^{close} \\ 0 & if \quad price_t^{close} = price_{t-1}^{close} \\ -V_t & if \quad price_t^{close} < price_{t-1}^{close} \end{cases} \tag{5}$$

### *Descriptive Statistics*

The results of descriptive statistics of the four technical indicators in terms of mean, standard deviation, skewness coefficients, kurtosis coefficients for the BTC, ETH, and XRP series are reported in Table 2. The results show that over the periods of study, the OBV indicator performs better in terms of average returns in all of the series with a mean of 56. 54, and 69, respectively. Also, the results in terms of medium indicate a higher OBV in all of the series. The standard deviation results do not differ significantly for RSI, MFI, STOCH, and OBV in all of the series.

## Normalizing the Data

The ranges of the statistical inputs are quite different; hence, it is necessary to standardize the dataset in a close range to create a faster teaching model. The study applied a z-score to alter data, which is the zero mean and standard deviation of the data.

$$Z = \frac{(x - \mu)}{\sigma} \tag{6}$$

**Table 2** Descriptive statistics

| BTC | | | | | |
|---|---|---|---|---|---|
| Variables | RSI | MFI | STOCH | OBV | Close Price ($) |
| Minimum | 9.9 | 5.8 | 0.0 | −332807330 | 178.10 |
| Maximum | 94.3 | 96.7 | 100.0 | 2687294800000 | 67566.83 |
| Mean | 53.6 | 54.2 | 55.4 | 567362797151 | 12154.47 |
| Median | 52.7 | 54.4 | 56.4 | 170575770000 | 6475.25 |
| Std. Dev. | 14.1 | 16.8 | 30.0 | 751280313788 | 16623.74 |
| Skewness | 0.2 | 0.0 | −0.1 | 1.17 | 1.66 |
| Kurtosis | −0.2 | −0.5 | −1.3 | −0.14 | 1.46 |
| ETH | | | | | |
| Minimum | 15.7 | 0.0 | 0.0 | −39702434000 | 84.31 |
| Maximum | 90.3 | 94.6 | 100.0 | 1789614200000 | 4812.09 |
| Mean | 51.5 | 53.0 | 52.7 | 547318359658 | 1079.15 |
| Median | 50.9 | 52.2 | 51.6 | 161411270000 | 396.41 |
| Std. Dev. | 14.1 | 17.2 | 30.1 | 651499246173 | 1259.29 |
| Skewness | 0.1 | 0.1 | 0.0 | 0.75 | 1.27 |
| Kurtosis | −0.3 | −0.5 | −1.3 | −1.16 | 0.23 |
| XRP | | | | | |
| Minimum | 19.7 | 4.8 | 0.0 | −-18672759000 | 0.139635 |
| Maximum | 93.5 | 96.9 | 100.0 | 264690070000 | 3.37781 |
| Mean | 48.7 | 49.0 | 44.4 | 69800103644 | 0.544315 |
| Median | 47.0 | 47.7 | 40.7 | 23107291000 | 0.408472 |
| Std. Dev. | 13.0 | 17.5 | 27.2 | 81490070915 | 0.386363 |
| Skewness | 0.7 | 0.3 | 0.3 | 0.99 | 2.142296 |
| Kurtosis | 0.5 | −0.3 | −1.1 | −0.75 | 7.907054 |

Note: Std. Dev. stands for Standard Deviation

## Methodology

### *The Architectural Design of the Proposed Model*

The proposed model is LSTM multi-input neural network model, which is not processing all the data simultaneously, instead, each data is processed and handed independently, then the processed data are merged and further utilized for estimating the final prediction. The aim of this method is to independently extract useful information from various datasets. The advantage of using this model is providing more flexibility and adaptivity for low computation efforts.

The architecture of the utilized Neural Networks is a four-layer LSTM with two fully connected (dense) layers applied, Leaky ReLU and Sigmoid Activation functions, respectively. Its loss function is the mean squared error with "ADagrad" optimizer algorithm. This study used 75% samples to train our LSTM multi-input neural network model and then validated it on 25% samples (under 50 epches and 56 batch size) (Fig. 2).

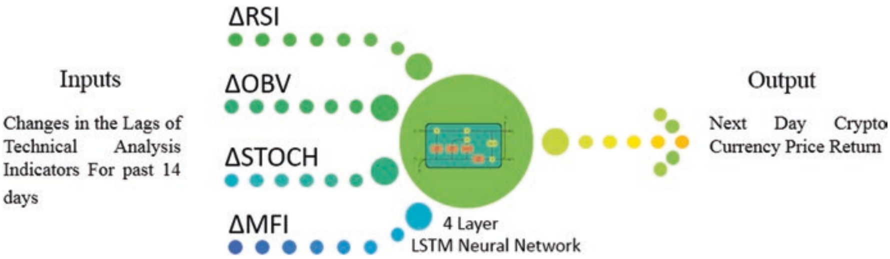



**Fig. 2** The overview architecture of the proposed model

| | | |
|---|---|---|
| #1 | Training (2014-2022), 2083 train 75% | Testing 695 test |

| | | |
|---|---|---|
| #2 | Training (2017-2022), 1219 train 75% | Testing 407 test |

| | | |
|---|---|---|
| #3 | Training (2017-2022), 1219 train 75% | Testing 407 test |

**Fig. 3** Training and testing process

### *Training and Testing Process*

To generate and then assess our model, we require to train and test the datasets. Also, we need to evade the problem of overfitting results by dividing time series data into numerous portions by adopting a sliding window over time.

We adopt three datasets (#1, 2, and 3) to have "three-fold cross-validation". We train 75% of the whole dataset (75% training was selected in order to avoid the problem of overfitting), and test the remaining 25%. In the graph below, the training and testing approach is illustrated. #1 shows the results of BTC, #2 depicts ETH, and #3 portrays XRP (Fig. 3).

## Performance Evaluation

Predicting the direction of the changes is very important, especially for trend trackers (Bai et al., 2015). Many trend-following trading techniques use the probability of trend direction in high-frequency timespans (Rechenthin & Street, 2013). As shown in the equation, we use a percentage of correct direction change prediction (%CDCP), which gives the proportion of correctly forecast directional changes given lead time $s$ (during the whole forecasting period).

$$\%\text{correct direction change prediction} = \frac{1}{T-(T_1-1)}\sum_{T}^{t=T_1} Z_{t+s} \tag{7}$$

Where $Z_{t+s}$'s are binary expressions come from below equations, $y_t$ and $y_{t+s}$ are realized values and $f_{t+s}$ are the forecast values.

$$Z_{t+s} = 1 \text{ if } (y_{t+s} - y_t)(f_{t+s} - y_t) > 0$$

$$Z_{t+s} = 0 \text{ otherwise}$$

These two measures help us to estimate the predicting efficiency of the proposed synergistic model relative to both stand-alone methods, namely, the technical analysis structural model and the intra-market model.

## *Empirical Results*

By applying the mentioned LSTM neural network model, after training 75% of sample data, 25% of the test sample for BTC, ETH, and XRP price returns are predicted as presented in Fig. 4.

Table 3 presents the statistical analysis performed by CDCP, MAE, and RMSE. More specifically, Table 3 provides statistical evidence that our proposed model can predict 63% correct directional changes of price for BTC. Meanwhile, 74% correct prediction of directional changes of the price of ETH. Finally, our model is able to forecast 77% of directional changes in the price of XRP.

MAE and RMSE, which are more popular in financial forecasting studies, have been also applied in our study (Draxler & Siebenhofer, 2014; Chortareas et al., 2011; Lahmiri, 2014).

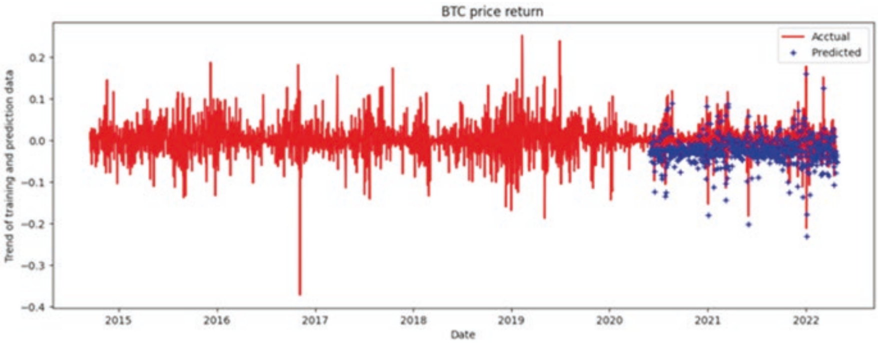
We also compare the predicting performance to the random walk benchmark method. The random walk model implies that future price changes are not predictable. Historical memory is not useful; it is just a series of random numbers (Fama, 1965).

The result of the percentage of correct direction change prediction (%CDCP) should be greater than 50% in order to validate the superior performance of the proposed model in comparison with the random walk model (Hong et al., 2007).

The critical value at a 1% statistical significance level can be approximated for the random walk model by the following equation (Cai & Zhang, 2016):

$$\sigma_{0.01\%} = \frac{\sim 3.719016}{2\sqrt{n}} \tag{8}$$

where $n$ is the number of predictions, and ½ comes from the equal probability of having positive and negative change. In our case, due to the different number of




(a) BTC


(b) ETH


(c) XRP

**Fig. 4** Daily price returns of cryptocurrencies BTC, ETH, XRP

observations, the critical values ($\sigma_{0.01\%}$) would be 0.03 and 0.04 for 2778 and 1626 observations, respectively.

In order to check the significance of the obtained forecasting results, according to *CDCP-50%* values in Table 3, all the values 0.13, 0.24, and 0.27 are greater than the critical values 0.03, 0.04, and 0.04, respectively, which means that all the obtained forecasting results are statistically significant.

**Table 3** The CDCP, MAE, and RMSE of BTC, ETH, and XRP

| Cryptocurrency | CDCP | CDCP-50% | Critical value at 1% ($\sigma_{0.01\%}$) | MAE (train period) | RMSE (test period) |
|---|---|---|---|---|---|
| BTC | 63% | 0.13 | 0.03 | 0.0756 | 0.05 |
| ETH | 74% | 0.24 | 0.04 | 0.1223 | 0.09 |
| XRP | 77% | 0.27 | 0.04 | 0.1413 | 0.20 |

## Conclusion

The study proposed a deep neural network method constructed by a multi-input architecture in order to forecast the next day's cryptocurrency prices.

The proposed forecasting model gets the benefit of different lags of four technical analysis indicators as inputs, which examine them separately in order to exploit and process each data independently.

Particularly, every technical analysis indicator's data contains inputs to various convolutional and LSTM layers, which are employed for learning the internal demonstration and determining the short-run and long-run dependencies of each cryptocurrency, respectively.

Subsequently, the model combines the refined data captured from the output vectors of LSTM layers and additionally develops them to create the final forecasting. It is worth mentioning that all of the applied cryptocurrency time series were transformed according to returns transformation so as to capture the stationarity characteristics and to be proper for fitting the proposed model.

We use three cryptocurrencies with the highest market capitalization, i.e., Bitcoin, Ethereum, and Ripple. The detailed experimental analysis illustrated that the proposed model has the ability to provide significant price movement forecasting, outperforming the traditional deep learning models with more precise price prediction.

More specifically, we reached 65% significate price prediction for bitcoin, and 74% significate price prediction for ETH, finally, 77% significate price prediction for XRP.

The results illustrate that the proposed method helps the investors to make more reliable decisions by significantly improving the prediction accuracy against the random walk over the maximum trading time of BTC, ETH, and XRP datasets.

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