Cryptocurrency price forecasting method using long short-term memory with time-varying parameters

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ABSTRACT

Numerous research have been done to predict cryptocurrency prices since cryptocurrency prices affect global economic and monetary systems. However, investigations using linear connection approaches and technical analysis indicators frequently fall short of providing an explanation for changes in the pattern of BitCoin pricing. This paper is proposed to study time-varying parameters with long short-term memory (LSTM). The study is investigated on a dataset retrieved from Binance from March 2022 to April 2022. The proposed LSTM used a variety of hyperparameter settings, particularly time parameters, to predict the cryptocurrency price (BTC/USDT) on the dataset. Additionally, it is evaluated in terms of mean absolute percentage error (MAPE) in comparison to smooth moving average (SMA), weighted moving average (WMA), and exponential moving averages (EMA). From the investigation, using the previous 3 days for prediction gives the lowest of the MAPE values and the proposed LSTM outperformed the other models. When considering the last three days' value of pricing, the indicated LSTM offers the best accurate prediction, with a MAPE percentage of 0.0927%.

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1. INTRODUCTION

An electronic or virtual currency known as a cryptocurrency is protected by encryption, making it nearly hard to forge or double spend [1], [2]. Among the most significant commodities in the world is cryptocurrency. Each cryptocurrency claims to have a distinct function and specification. For instance, Ethereum's ether positions itself as gas for the underlying smart contract platform. Banks use Ripple's XRP to make international payments easier. A total market cap of about $983.72 billion as of June 2022. It has had a significant effect on global monetary and economic systems. It stands for power, riches, and political influence as well as achievement and admiration. Cryptocurrency offers more competitive returns in the financial and investment sectors than other important financial assets. Its price does, however, fluctuate greatly. Understanding the fluctuation of cryptocurrencies is the first and most significant step in comprehending their risk attributes. It is also a key component of risk management, market making, portfolio optimization and selection, derivative pricing and hedging, and a number of other activities [3], [4].

Many works were proposed to study cryptocurrency characteristics and predict the cryptocurrency prices. According to the links between many parameters, there are two categories for the techniques used to forecast BitCoin values. Firstly, methods using machine learning techniques among factors to forecast cryptocurrency prices were widely found to determine cryptocurrency prices such as, time-series [5], support vector machine [6]–[8] wave theory [9], [10] random forest [7], binomial generalized linear model (GLM) [7], Bayesian neural network [11], auto-regression [12], autoregressive integrated moving average (ARIMA) [13], gradient boosting tree model [14]. For example, this study [11] examines the time series of the BitCoin process to highlight the impact of bayesian neural network (BNN). The root mean square error (RMSE) and mean absolute percentage error (MAPE) standards are used to evaluate the BNN model. In order to represent and anticipate the BitCoin process, the BNN is contrasted with a number of linear and nonlinear benchmark models. According to empirical studies, BNN is effective at predicting Bitcoin price time series and explaining the current cryptocurrency market's extreme volatility. Using data from Twitter and Google Trends, this paper [15] attempts to forecast price movements in Bitcoin and Ethereum. A linear model that incorporates tweets and Google Trends data was used to effectively forecast price volatility. By applying this approach, one may make more considered evaluations the buying and selling of Bitcoin and Ethereum.

In addition to other indicators, deep learning algorithms are used to predict BitCoin prices. Recurrent neural network (RNN) technology, which is based on deep learning, was widely used for predicting BitCoin prices [16]–[19]. For example, the goal of this paper [10] is to find out how accurately the direction of the Bitcoin price in US dollars can be predicted. Using a Bayesian-optimized RNN and long short-term memory (LSTM) network, the task is done to varying degrees of success. The LSTM model is assessed using the accuracy and RMSE standards. The study compared the performance of ARIMA models with that of deep learning, which includes both RNN and LSTM, and showed that deep learning outperformed ARIMA models. Then, this paper [20] studies statistical and deep-learning techniques to forecast the price of Bitcoin as well as the potential problem of network sentiments. It is specifically determined that sentiment is the most important factor in predicting Bitcoin market stocks by analyzing financial and sentiment aspects that were collected from economic and crowdsourced data. The LSTM model is assessed using the accuracy and mean squared error (MSE) standards. The study compared the performance of the RNN with auto-regressive integrated moving average with exogenous (ARIMAX), which found that the ARIMAX achieves better predictions than the RNN. Hamayel and Owda [21] proposed three types of RNN algorithms, gated recurrent unit (GRU), LSTM and bidirectional LSTM, for predicting the prices on datasets of Bitcoin, Litecoin and Ethereum. The models show excellent predictions of MAPE. All the models can present accurate results close to the actual cryptocurrency prices. The daily price of BitCoin was predicted using both the traditional LSTM model and the LSTM with AR (2) model in [22]. The experiment results show that LSTM with AR (2) gives excellent forecasting accuracy, MSE, RMSE, MAPE, and mean absolute error (MAE) for BitCoin price prediction. This article [23] proposed to forecast the Bitcoin prince by using public opinion on Twitter. It was discovered that the sentiment on Twitter is connected to Bitcoin Prince. Based on sentiment in BitCoin-related tweets and historical BitCoin prices, Random Forest Regression is used to predict Bitcoin values, and it has an accuracy rate of 62.48%. For predicting Bitcoin and Ethereum prices, [17] offers a multi-scale hybrid model. The cryptocurrency return series is first divided into subseries using the variational modal decomposition (VMD) approach. An extreme learning machine then uses the sparrow search algorithm to independently anticipate each subseries. The outcomes are finally calculated by adding the guesses together. The model improves the accuracy of cryptocurrency return forecasting effectively. This model could improve accuracy and more effectively than a single model.

From previous works, deep learning algorithms achieve the prediction of cryptocurrency prices because they can discover hidden patterns from historical cryptocurrency prices. Only a few research, however, focus on trade time and examine the relationship between factors for a deep learning algorithm in cryptocurrency price predictions. Although a period of time is very important, however, none of the research is considered. Therefore, this study prefers to apply a deep learning technique for the prediction of cryptocurrency. The prediction of cryptocurrency values uses LSTM, one of the most sophisticated deep-learning techniques that is commonly utilized for sequence learning applications like time-series prediction [24]. Besides the effective predictor, extracting good features should improve forecasting accuracy. Hence, time-varying parameters are comprehensively studied to predict cryptocurrency prices. For comparison with other existing techniques, the forecasting performance of LSTM is shown in MAPE, MAE, and RMSE metrics with different temporal parameter choices. In this paper, the contributions are; i) various periods of the day are studied for the training model by using the proposed LSTM model that gives the excellence prediction, and ii) various periods of minutes are studied for testing.

The remaining sections of this article are structured as follows: the history and related works are presented in section 2. The research technique is presented in section 3. Results and analysis are shown in section 4. The topic of future research accomplishes section 5.

2. THE COMPREHENSIVE THEORETICAL BASIS

2.1. Long short-term memory (LSTM)

Long-term memory RNNs, or LSTMs [18], are one kind of RNN. To address the vanishing gradient problem in RNNs, Hochreiter and Schmidhuber in 1997 [25] were the first to present the idea of gated units. RNNs are intriguing because of the potential connections between prior knowledge and a given task; for instance, using a prior word may help grasp a present sentence. This is similar to how people think. More specifically, RNNs have an internal state that, for a limited period of time, can convey context information about prior inputs. While adaptably taking contextual information into account, the input sequence is transformed into an output sequence. In complicated problem domain time series, such as machine translation, language modeling, and speech recognition, LSTM is frequently utilized. According to several studies, LSTM outperforms traditional time-series models for time-series forecasting. Thus, LSTM and convolutional neural networks (CNN) have been combined in many publications to estimate cryptocurrency prices. As a result, LSTM has a lot of promise for use in time-series forecasting, such as forecasting cryptocurrency prices.

In contrast to conventional RNNs, LSTM is a unique sort of RNN that can learn long-term dependencies. Information travels through mechanisms called cell states for LSTMs. LSTMs are capable of selective memory and forgetting. As seen in Figure 1, the cell state is the secret to LSTMs. In this study, i) x_t represents the input vector, ii) h_{t-1} represents output of a previous cell, iii) C_t represents cell memory of the current state, iv) C_{t-1} represents cell memory of a previous cell, v) C_t represents the candidate to a cell memory, vi) i_t represents input gate, vii) o_t represents output gate, viii) f_t represents forget gate, ix) g_t represents input gate, x) σ represents sigmoid function, xi) *Tanh* represents a hyperbolic tangent function, and xii) W^*, U^* represents associated weight matrices and 13) b^* represents biases. From Figure 1, two components can be identified as composing the LSTM's inner workings: i) current state (cell state) is the component that aids in state memorization in LSTM ,and ii) gate is a control of data flow (data flow) or analog value (analog) that allows LSTM to determine whether it is easier to remember data in each node or not, because the work in this part will help control the data that enters each node in the desired direction. Using the sigmoid function, the result of the cell preceding or hidden layer h_{t-1} is combined with x_t according to the specified weight of both layers and input into the cell state before C_{t-1}. The forward gate (f_t) layer that the sigmoid function passes through. It is paired with a cell state competitor ($\breve{C}_t$), which uses the tanh function to decide whether input data or knowledge from the previous cell state (C_{t-1}) is considered remembered or forgotten for storage in the current cell state. The data from the previous cell state (C_{t-1}) are taken into account and combined with the ot result via the sigmoid function to send to the next hidden layer or h_t hidden layer. LSTM consists of many parameters. Important LSTM network parameters as shown in Table 1. To achieve more consistent performance, all of these settings must typically be adjusted.

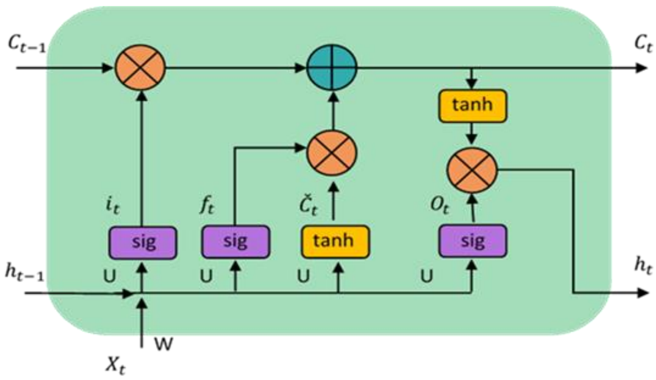


Figure 1. LSTM cell

Table 1. LSTM parameters

Parameter	Detail
Dropout	A regularization method for neural networks that reduces overfitting by preventing complex co-adaptations on training data [19].
Learning rate	An optimization algorithm's tuning parameter that determines the step size for each iteration as it approaches the minimum of the loss function [4].
Gradient descent	An iterative first-order approach for finding the local minimum of a differentiable function [4].
Loss function	A function that transforms an occasion or the values of one or more variables into a real number that intuitively represents the expense of the occasion [4].
Activation	The output of the function displays the probability distribution across several groupings.

2.2. Three fundamental types of moving averages

A calculation known as an smooth moving average (SMA) makes use of the arithmetic mean of a given set of prices over a predetermined period of time, such as 15, 30, 100, or 200 days. Weighted moving average (WMA) is a technical indicator that prioritizes recent data points over historical data, giving the latter less weight. The most recent prices are given more weight by exponential moving averages (EMA), but the rate of drop between prices is exponential rather than linear [26]. The SMA, WMA, and EMA formulas are depicted in (1)-(3), respectively, where A_i is the asset's price at period i, n is the total number of periods, and k is equal to $2/(n+1)$.

$$SMA = \frac{A_1+A_2+\cdots+A_n}{n} \tag{1}$$

$$WMA = \frac{A_1*n+A_2*(n-1)+\cdots+A_n}{\frac{n*(n-1)}{2}} \tag{2}$$

$$EMA = A_t * k + SMA_{t-1} * (1-k) \tag{3}$$

3. METHOD

The method of this study is explained in this section. First, data is collected from Binance lists on the website. Second, it is prepared as input for LSTM. The model is then built using the proposed LSTM, and a simulation was conducted to assess the proposed LSTM's performance. The method is briefly shown in Figure 2.

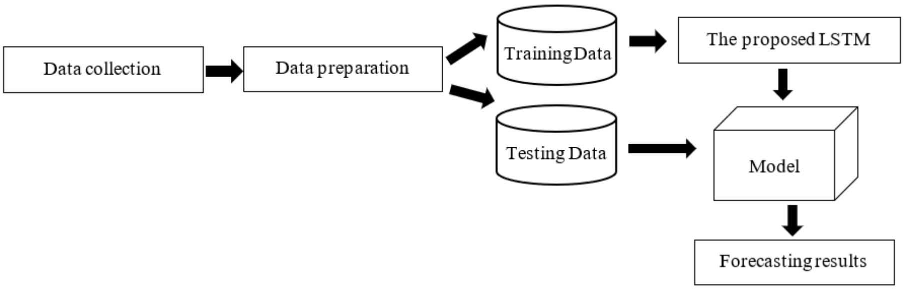


Figure 2. The research methodology

3.1. Data collection

The prices of BTC/USDT per minute are used to study in this paper. They are gathered from Binance lists from February 2022 to March 2022 [27]. Table 2 shows a list of the sample data that were gathered. For the purpose of constructing eight training datasets (from 15 February 2022 to 15 March 2022), a total of around 30 days' worth of data samples were employed. The eight training datasets are time-series datasets that were constructed using prices per minute from prior days and are set to 1, 3, 5, 10, 15, 20, 25, and 30. Three test datasets were kept for the final 240 minutes of data samples. The three test datasets are time-series datasets built from the price of prior minutes and are calibrated to anticipate the next 60, 120, and 240 minutes. A continuous number of days was determined for each feature.

Table 2. Ten-minutes sample data of cryptocurrency price

No.	Date	Clock	Prices
1.	2/15/2022	3:35	43617.66
2.	2/15/2022	3:34	43638.59
3.	2/15/2022	3:33	43633.58
4.	2/15/2022	3:32	43633.35
5.	2/15/2022	3:31	43657.63
6.	2/15/2022	3:30	43635.01
7.	2/15/2022	3:29	43611.25
8.	2/15/2022	3:28	43608.99
9.	2/15/2022	3:27	43584.9
10.	2/15/2022	3:26	43577.87

3.2. Data preparation

The process of preparing raw data for later processing and analysis is known as data preparation. All datasets must be translated into LSTM input data [28] before they can be used to fit an LSTM model. Figure 3 depicts the data transformation algorithm.

Input: Closing price datasets. Output: Forecasted GS_{P+1}, when P is the number of prediction minutes. Step1: Divide the chosen time-series datasets into input and output components as the first step. Step 2: Create a stationary time-series dataset using the chosen time-series datasets, which is easier to model and yields more accurate predictions.

Figure 3. Data-transformation algorithm

3.3. The proposed LSTM

A network structure of the proposed LSTM is shown in Figure 4. It has one LSTM unit and one hidden layer. Then, a straightforward LSTM was built with an output layer that had a linear activation function and output values. The value of prediction dates P was determined by the number of time steps over which a forecast was required. The dropout value was set at 0.2. The MAPE was also depicted as a network optimization technique and a loss function [29]. The batch size of the network was set at 16 for both forecasting and training.

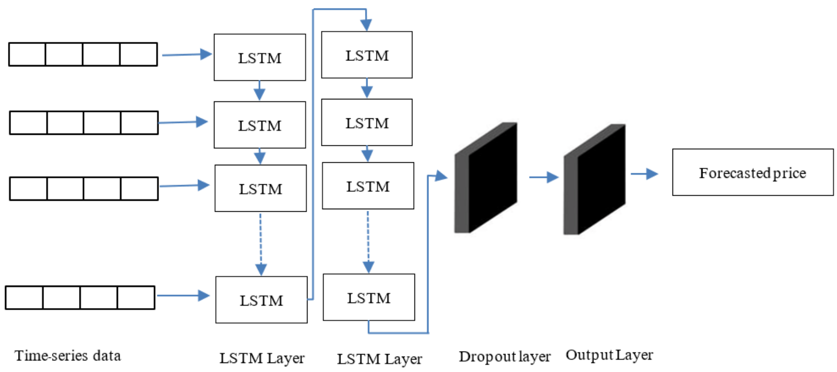


Figure 4. The structure of the proposed LSTM

3.4. Performance evaluation

The suggested approach is assessed using MAPE, MAE, and RMSE. The MAPE can be calculated by (4). The MAE can be calculated by (5). The RMSE can be calculated by (6), where A_i the actual cryptocurrency price, F_i is forecasted cryptocurrency price, and N is the number of samples.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|A_i - F_i|}{A_i}\right) \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A_i - F_i| \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(A_i - F_i)^2}{N}} \tag{6}$$

3.5. Simulation

This procedure aimed to use simulation to show the effectiveness of the suggested LSTM BitCoin price predicting approach. The NumPy and Pandas packages were used in the Python 3 code for the suggested forecasting technique. The parameters in Table 3 were used to present a particular circumstance in the simulation. The outcomes are contrasted with those obtained using SMA, EMA, and WMA as baseline procedures [30].

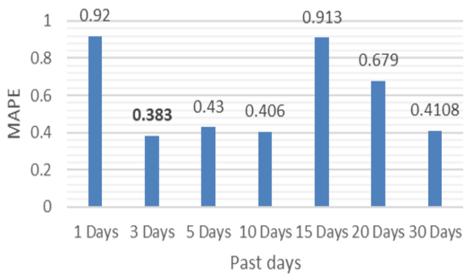
Table 3. Simulation parameters

Entities	Description	Detail/Range
Features	Characteristics utilized in simulation	price of cryptocurrency
Baseline	approaches to comparison	SMA, EMA, and WMA
Past days	The amount of time in the past (or present) that can be used to predict the future	1, 3, 5, 10, 15, 20, 25, 30 days
Forecasting minutes	The extended forecast minutes beyond the previously selected future dates	60, 120, 240 minutes
Dropout	A regularization method that's doing away with overfitting	0.2
Epoch	Training epoch	50 iteration
Optimizer	Network optimization method	Adaptive estimates of lower-order moments
Loss function	Measured error rate	MAPE, MAE, RMSE
Activation	Activation function	Relu, Softmax

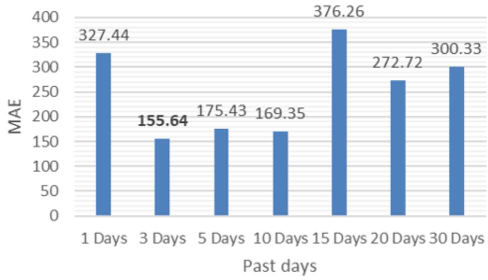
4. RESULTS AND DISCUSSION

The purpose of this experiment is to demonstrate the effectiveness of the proposed value-creation model in a simulated environment based on 100 model replications. The experimental findings are presented in relation to time's multidimensionality both the parameters for the previous day and the projected minutes, as well as comparisons to other indicators, are displayed.

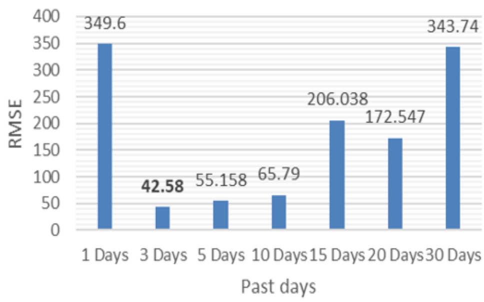
The MAPE, MAE, and RMSE values for various recent days are displayed in Figure 5. The lowest MAPE value when utilizing the last 3 days for forecasting is 0.383, as shown in Figure 5(a), which shows that MAPE values are generally low for the last 1 to 30 days. When utilizing the most recent 3 days for predicting, the lowest MAE value is 155.64, as shown in Figure 5(b), which shows that the MAE values are generally low throughout the prior 1 to 30 days. When utilizing the most recent 3 days for forecasting, the lowest RMSE value is 42.58, as shown in Figure 5(c), which shows that RMSE values are generally low throughout the prior 1 to 30 days. We ought to draw conclusions from the previous three days. The forecast horizon is widened because of price volatility. As a result, the time interval is set in minutes, which is suitable for investment, and the value is calculated using data from the previous three days. In conclusion, we should use the past three days. Due to price volatility, the forecast horizon is extended. So, the time interval is set in minutes, which is good enough for investing, and the last three days are used to figure out the current value.



(a)



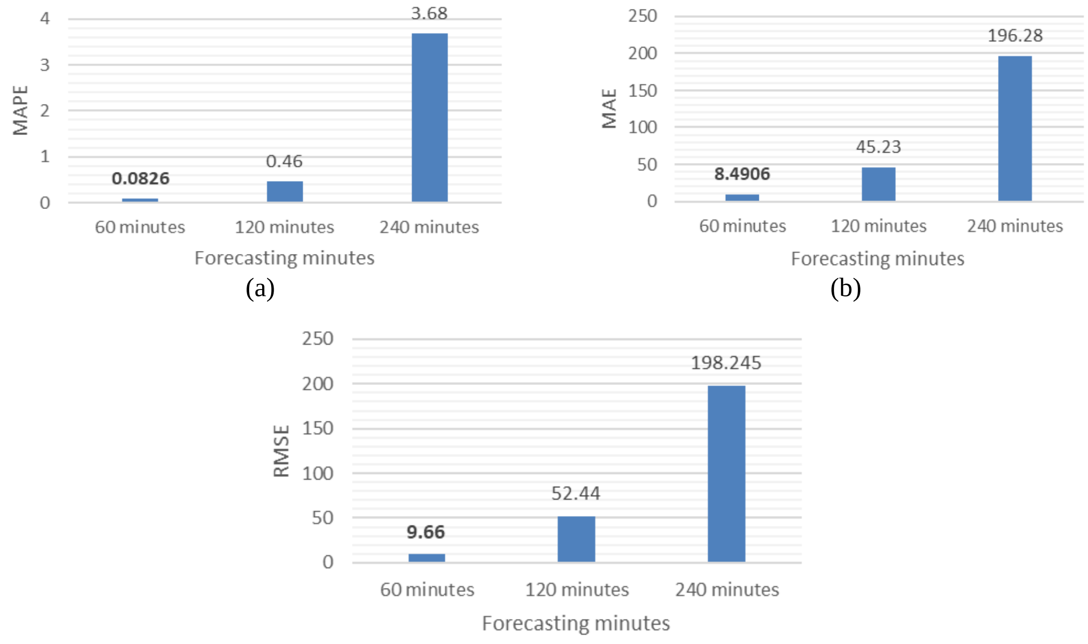
(b)



(c)

Figure 5. The difference past days of the LSTM model with (a) MAPE, (b) MAE, and (c) RMSE

Figure 6 shows the MAPE, MAE, and RMSE values on various forecasting minutes respectively. The Figure 6(a) depicts the MAPE values are relatively low during the forecasting 60, 120, and 240 minutes and the lowest MAPE value is 0.0826 when using forecasting 60 minutes. The Figure 6(b) depicts the MAE values are relatively low during the forecasting 60, 120, and 240 minutes using the past three days and the lowest MAE value is 8.4906 when using forecasting 60 minutes for forecasting. The Figure 6(c) depicts the RMSE values are relatively low during the forecasting 60, 120, and 240 minutes using the past three days and the lowest RMSE value is 9.66 when using forecasting 60 minutes.



(a) (b) (c)

Figure 6. The difference e forecasting minutes of the LSTM model with (a) MAPE, (b) MAE, and (c) RMSE

SMA, WMA, and EMA are used, as noted before, to compare the models to the baseline when the number of days in the past is set to 3. In Figure 7, the baseline is represented by the horizontal axis, and the MAPE error rate is shown by the vertical axis. The suggested LSTM system provides 0.000927 or 0.0927% of MAPE, which is the lowest MAPE when compared to the other baseline techniques. The LSTM is the most accurate for representing the data utilized in this investigation, according to the forecasted results. Figure 8 shows a comparison of the actual cryptocurrency price with price forecasts made over the forecasted minutes using (a) SMA, (b) EMA, (c) WMA, and (d) LSTM. Figure 8 demonstrates that the suggested LSTM generates cryptocurrency price predictions that are more accurate. Comparing the proposed LSTM model to the SMA, EMA, and WMA, the suggested LSTM model has the lowest MAPE, as shown in Figures 7 and 8. Furthermore, as compared to the SMA, EMA, and WMA, the suggested LSTM model has a comparatively low MAPE. In conclusion, throughout the previous three days and the sixty forecasting minutes, the values for MAPE, MAE, and RMSE were the lowest. Additionally, the proposed LSTM has the lowest MAPE value when compared to the baseline, and it accurately predicts the price of cryptocurrencies.

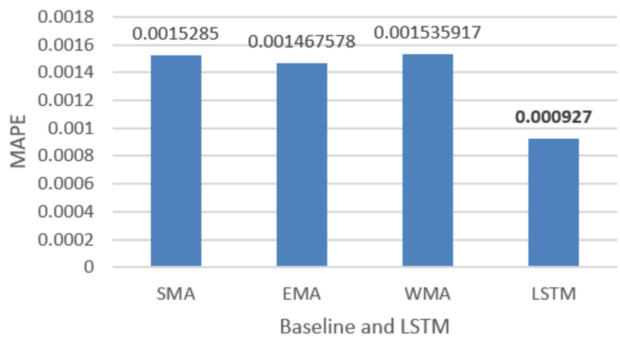


Figure 7. A comparison of MAPE of LSTM, SMA, EMA, and WMA

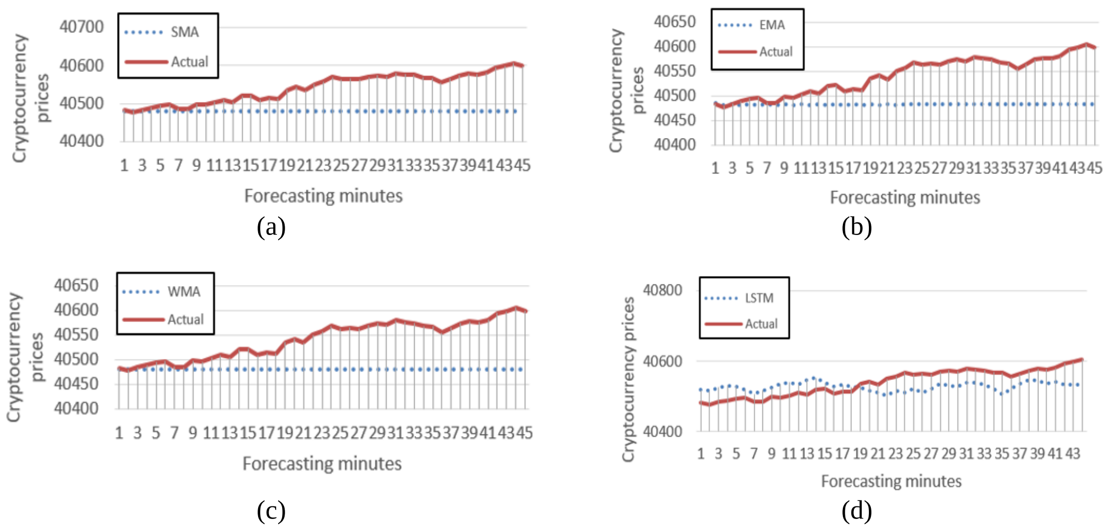


Figure 8. A comparison of actual cryptocurrency prices with (a) SMA, (b) EMA, (c) WMA, and (d) LSTM

5. CONCLUSION

This work presented a long, short-term memory (LSTM) system with time-varying characteristics to evaluate with period of time in predicting. Different scenarios were constructed and examined using simulation software based on previous days and predicted minutes. According to the simulation results, under various previous day and forecast-minute scenarios, the suggested LSTM model produces the lowest MAPE values. So, it is abundantly evident that for predicting cryptocurrency prices, it performs better than the SMA, WMA, and EMA. As a result, this experiment shows how important it is to use a guide when comparing the expected and real prices of cryptocurrencies. Additionally, we discovered that forecasting for 60 minutes and using data from the preceding three days can produce the greatest prediction outcomes. We anticipate expanding the suggested LSTM system to incorporate additional methods in the future to improve prediction precision.

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