Forecasting of Cryptocurrency Price and Financial Stability: Fresh Insights based on Big Data Analytics and Deep Learning Artificial Intelligence Techniques

Jihen Bouslimi
College of Administrative and Financial Sciences, Saudi Electronic University, Saudi Arabia
j.bouslimi@seu.edu.sa

Sahbi Boubaker
Department of Computer and Network Engineering, College of Computer Science and Engineering, University of Jeddah, Saudi Arabia
sboubaker@uj.edu.sa

Kais Tissaoui
Management Information Systems Department, Applied College, University of Ha'il, Saudi Arabia
k.tissaoui@uoh.edu.sa (corresponding author)

Received: 17 February 2024 | Revised: 22 March 2024 | Accepted: 6 April 2024

 DOI: https://doi.org/10.48084/etasr.7096

ABSTRACT

This paper evaluates the performance of the Long Short-Term Memory (LSTM) deep learning algorithm in forecasting Bitcoin and Ethereum prices during the COVID-19 epidemic, using their high-frequency price information, ranging from December 31, 2019, to December 31, 2020. Deep learning (DL) techniques, which can withstand stylized facts, such as non-linearity and long-term memory in high-frequency data, were utilized in this paper. The LSTM algorithm was employed due to its ability to perform well with time series data by reducing fading gradients and reliance over time. The obtained empirical results demonstrate that the LSTM technique can predict both Ethereum and Bitcoin prices. However, the performance of this algorithm decreases as the number of hidden units and epochs grows, with 100 hidden units and 200 epochs delivering maximum forecast accuracy. Furthermore, the performance study demonstrates that the LSTM approach gives more accurate forecasts for Ethereum than for Bitcoin prices, indicating that Ethereum is more prominent than Bitcoin. Moreover, the increased accuracy of forecasting the Ethereum price made it more reliable than Bitcoin during the COVID-19 coronavirus crisis. As a result, cryptocurrency traders might focus on trading Ethereum to increase their earnings during a crisis.

Keywords-cryptocurrency prices; COVID-19 pandemic; high-frequency data; LSTM approach; forecasting

I. INTRODUCTION

The cryptocurrency market and particularly Bitcoin price forecasting attract researchers and academicians. An accurate forecast of Bitcoin price is important for investors and policymakers [1], providing higher earnings and hedge against market risks. In addition, achieving accurate and effective forecasts requires the use of tools that can consider complex stylized facts, such as non-stationarity, randomness, nonlinearity, and hidden features of cryptocurrency price datasets. Several classical and advanced Artificial Intelligence (AI) tools are extensively investigated to predict Bitcoin prices [2]. Initially, many studies [3-5] supported traditional models such as GARCH and ARIMA. However, authors in [6-7] indicated that the classic models fail to generate good forecasting fits due to rigidity in terms of stationarity and heteroscedasticity. Others [2, 6, 8], supported the employment of Machine Learning (ML) tools and their extensions, namely Support Vector Regression (SVR), Regression Tree (RT), and Bayesian Regularization Neural Network (BRNN), which were reported to be robust in terms of prediction accuracy. Owing to the benefits of accurately forecasting Bitcoin price and due to the randomness of the cryptocurrency stock market, this study contributes to the optimization of portfolio, risk evaluation, and efficient trading by implementing smart forecasting frameworks of Bitcoin and Ethereum prices, during a pandemic crisis, such as that of COVID-19, using big data analytics and Deep Learning (DL) techniques. Due to their noise-resistant nature, DL techniques are regarded as efficient for time-series forecasting. They can learn non-linear temporal relationships on data sequences and provide native support for them [9]. As DL can consider the complex and hidden dynamics of the data, it has become a useful technique for predicting time series in volatile contexts [10]. DL's ability to automatically learn complicated characteristics and integrate massive quantities of data constitutes its key asset [11]. This realization was backed up by the authors in [12], who demonstrated that proving the stationary hypothesis is a prerequisite before engaging conventional statistical and econometric models to predict linear and nonlinear time series. For forecasting, non-stationary data must first be converted into stationary data. Thus, the predictive outcomes become less precise and effective. However, as ML and DL techniques have grown in popularity, their benefits in Bitcoin price prediction have become more apparent, since they do not rely on the assumption of stationary before the prediction process. Authors in [13] confirm this and provide evidence that DL is more flexible than the traditional forecasting tools. The former is a reliable technique that either functions as a hybrid approach or as a single approach to solve complicated problems with a lower error rate. Notwithstanding its benefits, the authors reported that the DL approach is still beset by the difficulty of determining the ideal arrangement for the models' structural configuration.

In addition, the DL techniques have shown robust forecasts in various domains, such as the commodity market [10, 14], the cryptocurrency market [12, 15], the gold market [16], and the coal market [17]. Due to the high ability of DL to forecast time series, this study investigates the performance of various DL algorithms in predicting Bitcoin and Ethereum price during the COVID-19 pandemic period by adopting the Long Short-Term Memory (LSTM) method as a DL tool. This research is undertaken to investigate the situation of the cryptocurrency market amid the COVID-19 outbreak. To achieve this, it is crucial to concentrate on researching the prices of major cryptocurrencies, specifically those of Bitcoin and Ethereum. This is accomplished by determining the stability of these currencies in the face of the initial wave of the coronavirus epidemic's global expansion. Furthermore, the emphasis on examining the price stability of digital currencies using high-frequency big data will help in the acquisition of a more rational and thorough picture of the cryptocurrency market. Reducing the level of panic among investors, who are astonished by the quick growth of the coronavirus and fear losing their investment portfolios, will be made easier with accurate predictions utilizing deep learning techniques.

Therefore, high-frequency price datasets of Bitcoin and Ethereum will be considered during the period that spans from 31/12/2019 to 31/12/2020. The use of the LSTM tool among other DL techniques is motivated by the latter's ability to perform well with time series data by reducing fading gradients and dependency over time [18]. In addition, the LSTM is implemented in this study owing to its capacity to recognize and retain patterns in time series data by including memory cells in its network structure [19]. What is more, the LSTM tool is a reliable big data tool capable of processing large quantities of observations at a high frequency [10].

This study's contribution compared to prior studies is summarized as follows. First, it is a pioneer study that examines the forecasting of Bitcoin prices during the pandemic period. As far as is known, no study has explored this subject during the pandemic through deploying high-frequency sampling of the intraday price data of Bitcoin and Ethereum with high frequency (one minute). Second, the current study will contribute to the recently emerging literature via implementing different DL techniques to forecast Bitcoin prices during a sudden outbreak because of the COVID-19 pandemic.

II. RELATED WORK

The cryptocurrency market is very volatile, uncertain, and unpredictable. It is continuously rising and sometimes dropping without warning. The high rate of price fluctuation is the main challenge of the bitcoin exchange rate. Due to their volatility and complexity, it is always difficult to predict the accurate price of cryptocurrencies [20]. Such prices can be affected by national and international regulations. As a consequence of its fluctuations, much research has been done on various cryptocurrencies to predict accurate prices. It has become necessary to develop a prediction tool to help investors make investment decisions in Bitcoin or other cryptocurrencies [21]. Authors in [22] reported that forecasting the price of Bitcoin has become an increasingly popular activity among investors and researchers because of the latter's attractive risk/reward profile. Authors in [8] predicted the price of Bitcoin, Digital Cash, and Ripple deploying DL techniques. Compared to the generalized regression neural architecture, the predictability of LSTM was found to be significantly higher. DL turns out to be highly efficient at predicting the inherently chaotic dynamics of cryptocurrency markets. LSTM systems were far better at learning chaotic and self-similar patterns for the three considered cryptocurrencies (Bitcoin, Digital Cash, and Ripple). Authors in [15] used a set of 40 explanatory variables to predict the price of Bitcoin following the Stacked Denoising Auto Encoders (SDAE) method. They concluded that the SDAE model outperforms the most popular machine learning methods, such as the SVR (Support Vector Regression), PCA-SVR (Principal Component Analysis-based SVR), and the BPNN (Back Propagation Neural Network) in both directional and level prediction. SDAE yielded the lowest MAPE and RMSE (0.1019 and 160.63, respectively) and the highest DA (0.5985). SVR provided the second-best performance, whereas the BPNN the worst. Authors in [22] implemented Gate-Recurrent Unit (GRU), LSTM, and bi-LSTM DL algorithms to estimate the value of Bitcoin, Litecoin, and Ethereum. The former found that the GRU outperformed LSTM and bi-LSTM, with the lowest RMSE. However, overall, all the algorithms produced high prediction results. Authors in [21] employed DL techniques LSTM and Recurrent Neural Networks (RNNs) to predict the Bitcoin price. Their models exhibited a better performance of the LSTM algorithm for predicting time-series cryptocurrency price, but it was reported to take more time to compile. Using the Interval Graph (IG)-Artificial Neural Networks (ANN) model, authors in [23] showed the outperformance of this model over the traditional ANN techniques in predicting the Bitcoin price. Authors in [24] proposed a hybrid regression model, the 1DCNN-GRU model, which consists of a merge of a One-Dimensional Convolutional Neural Network (1DCNN) and a stacked GRU. They concluded that this model outperformed the existing methods with the lowest RMSE value of 43.933. Authors in [20] predicted the price of Litecoin and Zcash utilizing a DL-based hybrid model that includes LSTM and GRU with an inter-dependent relation to the parent currency. Their results revealed high accuracy of price forecasting compared to that of the existing models. Authors in [25] predicted Bitcoin price direction utilizing the Random Forest (RF) method, which demonstrated a higher degree of accuracy than logit models. Their results indicated a prediction accuracy between 75% and 80% for a five-day prediction and more than 85% for a 10-day to 20-day forecast. Recently, authors in [26] resorted to using LSTM, GRU, and Bi-LSTM to estimate the price of three cryptocurrencies: Bitcoin, Ethereum, and Litecoin. They proved that Bi-LSTM performed better than LSTM and GRU regarding prediction accuracy. Authors in [27] estimated the price of five popular cryptocurrencies: XRP, Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), and Monero (XMR) by putting many tools into service, including ML, DL, and ensemble methods. They displayed that the DL approaches outperform the others in predicting the price of these five cryptocurrencies. The LSTM is the most powerful approach, while it costs less for the former to be trained in contrast to the other DL approaches.

III. METHODOLOGY

A. Long Short-Term Memory (LSTM)

LSTM, a subclass of DL, is an outstanding model that can learn from experience by modeling complicated connections through long-range series [17]. LSTM is adopted in this study for predicting the price of two popular cryptocurrencies, Bitcoin and Ethereum. LSTM was found through numerous studies to be suitable to tackle classical ML drawbacks such as the vanishing/exploding gradients problem. The solution provided by LSTM to this challenge is implemented using the concept of forget gates. The fundamental structure of an LSTM cell consists of input, output, and forget gates. The input gate oversees determining which data is received and subsequently passed to the cell. The forget gate regulates the quantity of information to be ignored (and hence prevented from entering the cell). The data are subsequently transferred to the output gate, which is in charge of producing the cell output and state. Mathematically, the LSTM operation is expressed by (1)-(5) [28]:

$$\mathrm{f_t} = \alpha(\mathrm{w_f}.[\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_f}) \quad (1)$$

$$\mathrm{i_t} = \alpha(\mathrm{w_i}.[\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_i}) \quad (2)$$

$$\mathrm{o_t} = \alpha(\mathrm{w_o}.[\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_o}) \quad (3)$$

$$\mathrm{C_t} = \mathrm{f_t C_{t-1}} + \mathrm{i_t}.\mathrm{th}(\mathrm{w_c}.[\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_c}) \quad (4)$$

$$h_t = O_t.\beta(C_t) \quad (5)$$

The interested reader can refer to [28] and the references therein for more details about the LSTM algorithm.

B. LSTM hyperparameter Setting

Although it exhibited high capability in forecasting time series, the LSTM algorithm (like any other neural network) has the limitations of difficult hyperparameter tuning and the dependence on many factors [17]. Hyperparameter setting in LSTM is a critical issue since there is no systematic procedure to select the latter. In the literature, several methods, such as Random Search (RS), Bayesian Optimization (BO), Genetic Algorithm (GA), and Grid Search (GS) have been used to tune the LSTM hyperparameters, like learning rate, number of units, input length, and number of epochs. However, those techniques are known to add more complexity to the training process (which is already computationally expensive) in addition to the fact that they require preliminary knowledge of at least the ranges of the hyperparameters. To overcome this drawback and since there is no prior expertise on the LSTM parameters, this study adopted the simplest trial-and-error method, which is benefited from the high robustness of the LSTM against its hyperparameter changes. Moreover, an LSTM algorithm with a specific hyperparameter tuning is not generically extendable to other case studies. A parameter set may provide good accuracy for a dataset and bad performance for another one even when forecasting the same time series in a different time window. In this study, several trial-and-error runs for the LSTM algorithm have been conducted. The LSTM accuracy metrics for the two cryptocurrencies' prices under study were recorded. A careful study of those performance indicators facilitated the tuning of the LSTM optimal hyperparameters, provided in Table I below.

TABLE I. ADOPTED LSTM HYPERPARAMETERS

Parameter	Value	Meaning
Units	50 and 100	Number of cells in the LSTM.
Activation function	Relu	Returns a value if the input is greater than 0. If not, it returns 0.
Batch-size	512	Used to distinguish the common features of the input data.
Epochs	100, 200, 500, 1000	Number of iterations for the training phase.
Scaler	Min-Max	Allows to scale the data within the interval [-1,1].
Optimizer	Adam	The adaptive moment (Adam) estimation is an improved descent algorithm for training the LSTM.

C. Performance Metrics

As usually occurs in forecasting, the dataset has been divided into 80% for training and 20% for validation [13]. In this paper, three performance metrics were adopted to determine the accuracy of the investigated approaches [15]:

- Mean Absolute Percentage error (MAPE):

$$\mathrm{MAPE} = \frac{100}{N}\sum_{t=1}^{N}\frac{|y(t)-\hat{y}(t)|}{\bar{y}} \quad (6)$$

- Coefficient of determination (R^2):

$$\mathrm{R}^2 = 1 - \frac{\frac{1}{N_2}\sum_{t=1}^{N}(y(t)-\hat{y}(t))^2}{\frac{1}{N}\sum_{t=1}^{N}(y(t)-\bar{y})^2} \quad (7)$$

The Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y(t) - \hat{y}(t))^2} \qquad (8)$$

where $\hat{y}(t)$ and $y(t)$ indicate respectively the predicted and the real cryptocurrency price on the t^{th} day, and $\bar{y}$ is the average value of the same price over the testing/validation period. The validation sample includes N observations.

IV. EMPIRICAL RESULTS

A. Data Analysis

The high-frequency (a dataset of a frequency of 1 min is used in this study) data sample includes a series of cryptocurrency assets, consisting of the Bitcoin and Ethereum prices. The selected data ranged from December 31, 2019 (the beginning of the COVID-19 epidemic) to February 14, 2020. The main focus of this study was to detect the effect of crises such as health pandemics on the fluctuation of the cryptocurrencies' prices. The dataset has therefore covered the period during which the COVID-19 pandemic has reached its most alarming effect. The time frame from January to February 2020 is regarded as the first instance in which the coronavirus spread over the world. As a result, investors are not only concerned about losing their investment portfolios, but also about the collapse of the cryptocurrency industry. Thus, selecting this era is crucial to determine how stable these currencies are and whether they can be more precisely forecasted considering the pandemic shock created by the epidemic, allowing investors to rest certain that their digital wallets will be secure in the short run. Hence, for each of the two series, 65535 observations were collected. The two series were separated into two sub-samples. The first subsample included 80% of the data, which corresponded to 52428 observations utilized for learning the LSTM DL algorithms. The validation processes were run on the second subsample, which had 13107 observations. Big data usage is crucial in all the spheres of business and finance. Accordingly, due to the coronavirus pandemic's quick spread and the high-speed information frequency linked to it, big data were employed from high-frequency cryptocurrency prices in this study. Because of the rapidity of the coronavirus pandemic's influence on the cryptocurrency market, big data needed to be leveraged from cryptocurrencies to demonstrate the former's scope. However, to efficiently evaluate and process these high-frequency data and derive actionable insights that will benefit investors and decision-makers, creative, efficient, and unorthodox techniques like DL must be employed. This study will be able to obtain more accurate findings by combining DL techniques with high-frequency big data, such as transaction data, rather than relying just on daily or monthly data that may overlook crucial information about intraday price trends.

The statistical explorative analysis provided in Table II demonstrates that all indices' skewness values deviate from zero, indicating that the distributions are asymmetrical. Furthermore, the kurtosis results were less than 3. This reveals that, for all variables, the distribution of digital currency assets has smaller tails than those of normal distributions. This finding implies that the data are nonlinear. Table III depicts the stationarity test results for all series. One important finding of the observations made was that all the Bitcoin variables had a unit root which stipulates the existence of fluctuations and cryptocurrency price instability. The results for the Phillips-Perron statistic and Augmented Dickey-Fuller are greater than the critical levels, indicating that the series data deviated further from zero. That is, the entire series demonstrated long-memory behavior. Authors in [10, 30-32] manifested that the existence of non-linear structures and long-memory patterns in dynamic systems can be attributed to the inside variables of the system itself. To address this matter, it is important to incorporate a non-linear dynamic approach into forecasting issues since this type of modeling tool does not require any modification/pre-processing of the original data. Therefore, it may be reasonable for researchers to use a non-linear dynamic approach as part of their forecasting tools to deal with this issue, since this type of model does not necessitate a transformation of the original data. Furthermore, the existence of stylized facts such as non-linearity and long-memory patterns motivates this study to use DL tools, like LSTM deep neural networks that are robust to those anomalies in data. The critical values for Phillips-Perron statistic and Augmented Dickey-Fuller tests calculated for the studied time series are: -3.43, -2.86, and -2.56 for 1%, 5%, and 10%, respectively.

TABLE II. DESCRIPTIVE STATISTICS

Price	Mean	Max	Min	S. D	Skew	Kurt
Bitcoin	8723.610	10519.83	6858.220	896.58	-0.079	2.18
Ethereum	179.4	289.57	125.6	41.7	0.949	2.95

SD: Standard Deviation, Skew: skewness, Kurt: kurtosis, Min: minimum, and Max: maximum. The sampling period runs from December 31, 2019 to February 14, 2020.

TABLE III. UNIT ROOT TEST

Price	Augmented Dickey-Fuller test statistic	Phillips-Perron test statistic
Bitcoin	-0.9135(0.7846)	-0.8623(0.8005)
Ethereum	-0.2189(0.9336)	-0.1218(0.9454)

Sampling period runs from December 31, 2019 to February 14, 2020.

B. Forecasting Analysis

Figures 1–10 depict all the predictions of cryptocurrency prices using the validation sets. As shown in the graphics, the estimate of the adopted LSTM DL algorithm exhibits that all the blue curves (prediction values) were close to the red curve (actual values) for all the cryptocurrency prices. The proposed LSTM approach demonstrated good follow-up behavior throughout the validation phase. More notably, the lines indicating the actual price and the forecasted price for all the cryptocurrency prices during the COVID-19 epidemic period are quite similar even though this period was characterized by significant volatility in many economic variables throughout the world. Furthermore, the results suggest that the LSTM technique is successful in creating forecast pricing curves during the initial phases of the coronavirus pandemic's spread. However, when the prices were extremely volatile throughout the intensity of the coronavirus epidemic, this high level of accuracy has been decreased. This supports the findings of [10] for the commodity market. When the number of hidden units was fixed at 50 and the number of epochs doubled from 500 to

1000, an improvement in the accuracy of forecasting both Bitcoin and Ethereum was noticed. It turns out that the gap between the predicted values and the current values for 500 epochs (Figures 1 and 2) is big. However, as the number of epochs increased to 1000 (Figures 4 and 5), the LSTM method provided more accurate predictions. That improvement appears more emphatically in Ethereum, as there is a smaller gap between the real curve (in red) and the prediction curve (in blue). According to the above results, LSTM has revealed a very similar trend and similar forecasts for both currencies. This means that the LSTM method has comprehensive accuracy over the entire verification period. This study's findings support the findings of [20, 26], according to which DL tools can accurately forecast bitcoin values although it should be mentioned that they disclosed that the Bi-LSTM performed better in predicting the cryptocurrency prices than LSTM. At the next stage, the number of hidden units was increased from 50 to 100. For the Bitcoin price, it was observed that as the number of hidden units is augmented, the accuracy of the forecasting decreases.

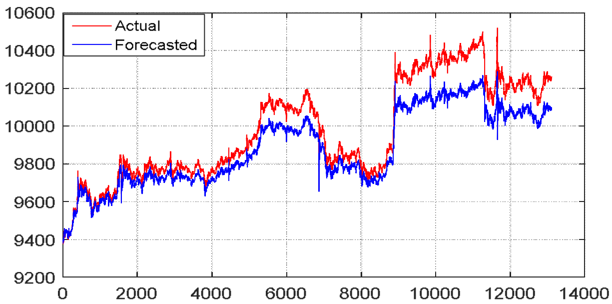

Fig. 1. Forecasting Bitcoin prices, 50 units, 500 epochs.

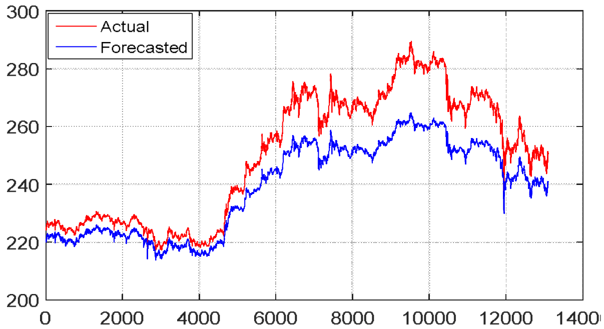

Fig. 2. Forecasting Ethereum prices, 50 units, 500 epochs.

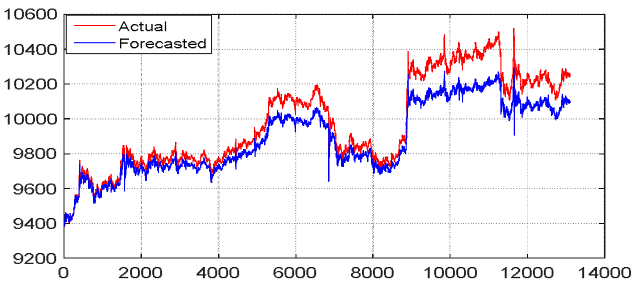

Fig. 3. Forecasting Bitcoin prices, 50 units, 1000 epochs.

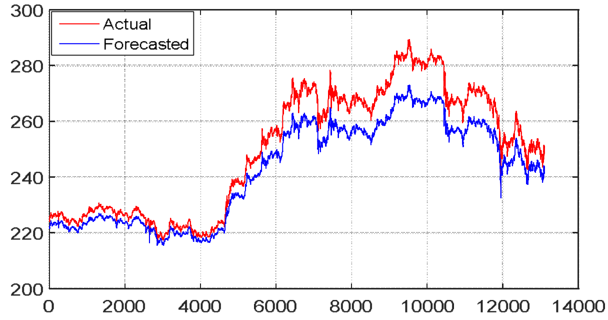

Fig. 4. Forecasting Ethereum prices, 50 units, 1000 epochs.

Figures 5, 7, and 9 provide evidence that, when the number of epochs is raised to respectively 100, 200, and 500, the gap between the real curve (in red) and the prediction curve (in blue) progressively rises. Hence, the LSTM tool remains robust to forecast Bitcoin, but this goodness declines with the increase of hidden units and epochs. For the Ethereum price, the results are different. For 100 hidden units and 100 epochs (Figure 6), there is an important fluctuation between the real curve (in red) and the prediction (in blue), meaning a decrease in the accuracy of forecasting. However, it can be observed that the real curve and the prediction curve have the same behaviors when the number of epochs is increased to reach 200 (Figure 8). This indicates that the forecasting power of LSTM improves. However, this improvement has been reduced in the case of 500 epochs (Figure 10). There is an important fluctuation between the real curve and the prediction curve. Similarly to the Bitcoin results, the LSTM tool remains robust in forecasting the price of Ethereum, but this excellence declines with the increase of hidden units and epochs, except in the case of 100 hidden units and 200 epochs, where the forecast accuracy reaches the optimum.

Overall, it is highlighted that the LSTM tool generates a better fit in the case of Ethereum than in the case of Bitcoin, indicating that the Ethereum asset is dominant compared to the Bitcoin asset and it is more accurately predicted during the COVID-19 coronavirus crisis. This study's findings are consistent with those of [33-34], who demonstrate that the LSTM tool can handle issues involving both long-term and short-term dependence memory.

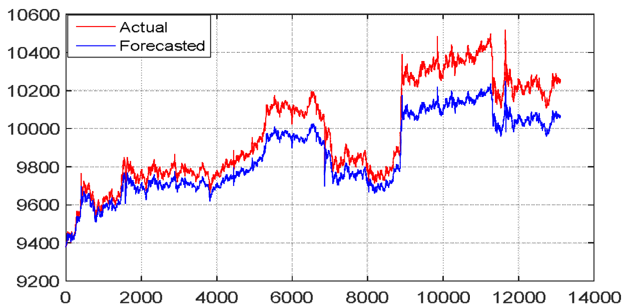

Fig. 5. Forecasting Bitcoin prices, 100 units, 100 epochs.

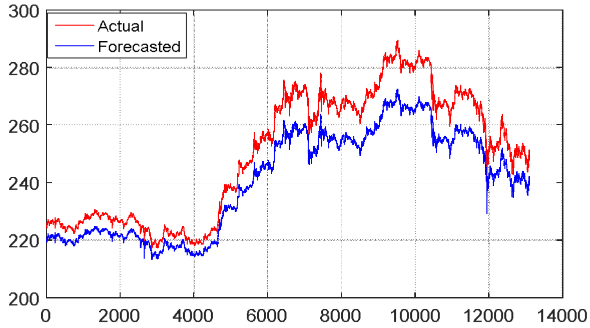

Fig. 6. Forecasting Ethereum prices, 100 units, 100 epochs.

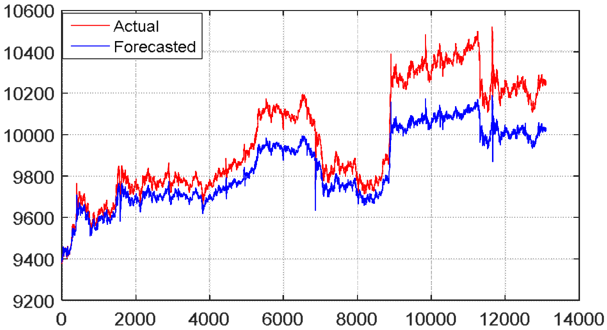

Fig. 7. Forecasting Bitcoin prices, 100 units, 200 epochs.

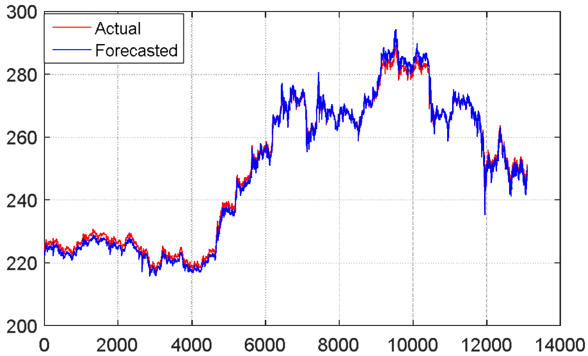

Fig. 8. Forecasting Ethereum prices, 100 units, 200 epochs.

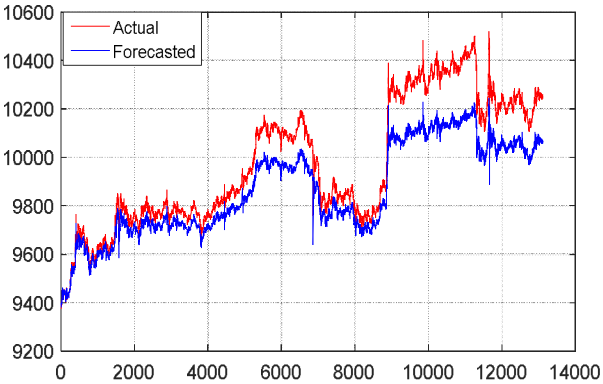

Fig. 9. Forecasting Bitcoin prices, 100 units, 500 epochs.

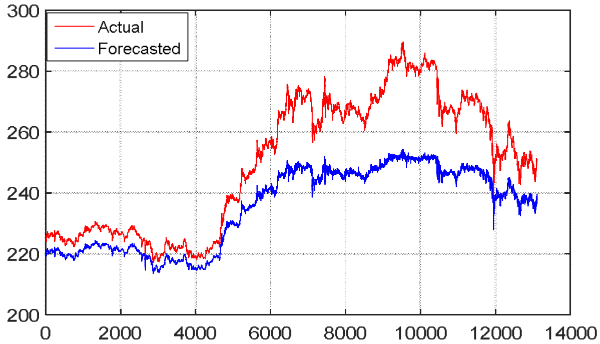

Fig. 10. Forecasting Ethereum prices, 100 units, 500 epochs.

V. PERFORMANCE ANALYSIS

Table IV displays the proposed forecast tool's performance metrics MAPE, RMSE, and R^2 for both Bitcoin and Ethereum prices. Overall, this table indicates that the LSTM model produces a satisfactory forecast, supporting the findings noticed in Figures 1-10. When the hidden units were fixed at 50 and the epochs were altered from 500 to 1000, it can be observed that the values of performance metrics improved. Empirically, the LSTM model provides lesser RMSE and MAPE values and higher R^2 in the case of 1000 epochs than in that of 500 epochs for both Bitcoin and Ethereum. It was discovered that the performance metrics of Bitcoin prices are better than those of Ethereum prices, highlighting that initially Bitcoin is best forecasted. However, when the hidden units were increased from 50 to 100 and the epochs from 100 to 200 and 500, the findings were different. For Bitcoin, a higher value of MAPE and RMSE metrics and a lower value of R^2 in the case of 50 hidden units are detected compared to those with 100 hidden units. This means that the performance of the LSTM tool in forecasting the Bitcoin price becomes worse when the hidden units are increased. Concerning the Ethereum prices, diverse findings are observed. The values of performance metrics are unstable. For 100 hidden units and 100 epochs, the values of MAPE, RMSE, and R^2 are 3.7265%, 10.1294$, and 78.33%, respectively. When the number of epochs is raised, the values of these metrics significantly improve to 0.5318%, 1.5560$, and 99.49%, accordingly.

When the epoch number was increased to 500, the performance of the LSTM tool declined. The values of MAPE, RMSE, and R^2 became 5.8264%, 17.1148$, and 38.13%. Furthermore, when 100 hidden units were considered, the performance indicators of Ethereum prices outperformed those of the Bitcoin prices. Overall, the LSTM findings showed that during the COVID-19 pandemic crisis, the Ethereum asset was dominant in terms of forecast and performance competence, especially when considering an increase of the hidden units of the LSTM. These findings are consistent with those in [27], which showed that the LSTM is the most powerful approach, and costs less to train than other DL approaches. The particular findings, however, are not consistent with [22], which demonstrated that the GRU fared better in forecasting cryptocurrency prices than the LSTM and bi-LSTM with the lowest RMSE.

TABLE IV. PERFORMANCE RESULTS

Case	Units	Epochs	Bitcoin			Ethereum		
			MAPE (%)	R^2 (%)	RMSE ($)	MAPE (%)	R^2 (%)	RMSE ($)
1	50	500	0.955	81.1	112.822	4.331	66.9	12.505
2	50	1000	0.901	82.7	108.074	2.971	84.6	8.5387
3	100	100	1.179	73.2	134.574	3.7265	78.33	10.1294
4	100	200	1.375	61.58	161.24	0.5318	99.49	1.5560
5	100	500	1.102	74.56	131.1	5.8264	38.13	17.1148

VI. CONCLUSION AND FINANCIAL IMPLICATIONS

The forecasting of cryptocurrencies has considerably changed over the last decades with the development of machine learning and deep learning tools. Having a successful cryptocurrency forecast depends on understanding the dynamics of the price and how it is generated. This is an important topic for both regulators and investors to take into account when managing portfolio risks. However, achieving this goal necessitates developing and implementing forecasting methods that can withstand a wide range of economic, geopolitical, and health variables, the most significant of which occurred during the recent years. Some of these variables include the spread of the coronavirus and the conflict between Russia and Ukraine. This research investigates the forecasting power of the LSTM deep learning tool for Bitcoin and Ethereum prices using big data analytics during the COVID-19 pandemic crisis.

The main findings of the current analysis are:

- First, there was an urge to apply deep learning methods like LSTM deep neural networks that are resilient to certain stylized facts in data like non-linearity and long memory.
- Second, the LSTM tool is capable of forecasting both Ethereum and Bitcoin, but its goodness decreases as the number of hidden units and epochs increases, with 100 hidden units and 200 epochs being the settings where the forecast accuracy achieves its highest level.
- The LSTM method produces more accurate predictions for Ethereum than for Bitcoin, showing that Ethereum is more predominant than Bitcoin and can be forecasted more precisely during the COVID-19 coronavirus crisis.
- Furthermore, the findings of this study have implications for crypto traders that require precise high-frequency forecasts amid crises like the coronavirus pandemic outbreak. Consequently, the aforementioned findings revealed that Ethereum is detected with the highest accuracy by LSTM, making it more stable than Bitcoin during the coronavirus crisis. For this reason, cryptocurrency traders can concentrate on trading Ethereum to boost their profits during crises.

ACKNOWLEDGEMENT

'The authors extend their appreciation to the Deanship of Scientific Research at Saudi Electronic University for funding this research (8285).

REFERENCES

[1] S. A. Gyamerah, "On forecasting the intraday Bitcoin price using ensemble of variational mode decomposition and generalized additive model," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 3, pp. 1003–1009, Mar. 2022, https://doi.org/10.1016/j.jksuci.2020.01.006.

[2] R. K. Jana, I. Ghosh, and D. Das, "A differential evolution-based regression framework for forecasting Bitcoin price," *Annals of Operations Research*, vol. 306, no. 1, pp. 295–320, Nov. 2021, https://doi.org/10.1007/s10479-021-04000-8.

[3] P. Katsiampa, "Volatility estimation for Bitcoin: A comparison of GARCH models," *Economics Letters*, vol. 158, pp. 3–6, Sep. 2017, https://doi.org/10.1016/j.econlet.2017.06.023.

[4] K. Tissaoui, T. Zaghdoudi, and K. I. Alfreahat, "Can intraday public information explain Bitcoin Returns and Volatility? A PGARCH-Based Approach," *Economics Bulletin*, vol. 40, no. 3, pp. 2085–2092, 2020.

[5] A. Azari, "Bitcoin Price Prediction: An ARIMA Approach." arXiv, Apr. 04, 2019, https://doi.org/10.48550/arXiv.1904.05315.

[6] I. Ghosh, M. K. Sanyal, and R. K. Jana, "Analysis of Causal Interactions and Predictive Modelling of Financial Markets Using Econometric Methods, Maximal Overlap Discrete Wavelet Transformation and Machine Learning: A Study in Asian Context," in *Pattern Recognition and Machine Intelligence*, 2017, pp. 664–672, https://doi.org/10.1007/978-3-319-69900-4_84.

[7] A. C. da Silva Filho, N. D. Maganini, and E. F. de Almeida, "Multifractal analysis of Bitcoin market," *Physica A: Statistical Mechanics and its Applications*, vol. 512, pp. 954–967, Dec. 2018, https://doi.org/10.1016/j.physa.2018.08.076.

[8] S. Lahmiri and S. Bekiros, "Cryptocurrency forecasting with deep learning chaotic neural networks," *Chaos, Solitons & Fractals*, vol. 118, pp. 35–40, Jan. 2019, https://doi.org/10.1016/j.chaos.2018.11.014.

[9] J. Brownlee, *Deep Learning for Time Series Forecasting: Predict the Future with MLPs, CNNs and LSTMs in Python.* Machine Learning Mastery, 2018.

[10] H. Ben Ameur, S. Boubaker, Z. Ftiti, W. Louhichi, and K. Tissaoui, "Forecasting commodity prices: empirical evidence using deep learning tools," *Annals of Operations Research*, Jan. 2023, https://doi.org/10.1007/s10479-022-05076-6.

[11] Z. Alshingiti, R. Alaqel, J. Al-Muhtadi, Q. E. U. Haq, K. Saleem, and M. H. Faheem, "A Deep Learning-Based Phishing Detection System Using CNN, LSTM, and LSTM-CNN," *Electronics*, vol. 12, no. 1, Jan. 2023, Art. no. 232, https://doi.org/10.3390/electronics12010232.

[12] C. Jin and Y. Li, "Cryptocurrency Price Prediction Using Frequency Decomposition and Deep Learning," *Fractal and Fractional*, vol. 7, no. 10, Oct. 2023, Art. no. 708, https://doi.org/10.3390/fractalfract7100708.

[13] F. Aksan, Y. Li, V. Suresh, and P. Janik, "CNN-LSTM vs. LSTM-CNN to Predict Power Flow Direction: A Case Study of the High-Voltage Subnet of Northeast Germany," *Sensors*, vol. 23, no. 2, Jan. 2023, Art. no. 901, https://doi.org/10.3390/s23020901.

[14] J. S. Kamdem, R. B. Essomba, and J. N. Berinyuy, "Deep learning models for forecasting and analyzing the implications of COVID-19 spread on some commodities markets volatilities," *Chaos, Solitons & Fractals*, vol. 140, Nov. 2020, Art. no. 110215, https://doi.org/10.1016/j.chaos.2020.110215.

[15] M. Liu, G. Li, J. Li, X. Zhu, and Y. Yao, "Forecasting the price of Bitcoin using deep learning," *Finance Research Letters*, vol. 40, May 2021, Art. no. 101755, https://doi.org/10.1016/j.frl.2020.101755.

[16] A. Vidal and W. Kristjanpoller, "Gold volatility prediction using a CNN-LSTM approach," *Expert Systems with Applications*, vol. 157, Nov. 2020, Art. no. 113481, https://doi.org/10.1016/j.eswa.2020.113481.

[17] Z. Alameer, A. Fathalla, K. Li, H. Ye, and Z. Jianhua, "Multistep-ahead forecasting of coal prices using a hybrid deep learning model," *Resources Policy*, vol. 65, Mar. 2020, Art. no. 101588, https://doi.org/10.1016/j.resourpol.2020.101588.

[18] Z. Alshingiti, R. Alaqel, J. Al-Muhtadi, Q. E. U. Haq, K. Saleem, and M. H. Faheem, "A Deep Learning-Based Phishing Detection System Using

CNN, LSTM, and LSTM-CNN," *Electronics*, vol. 12, no. 1, Jan. 2023, Art. no. 232, https://doi.org/10.3390/electronics12010232.

[19] M. Gabriel and T. Auer, "LSTM Deep Learning Models for Virtual Sensing of Indoor Air Pollutants: A Feasible Alternative to Physical Sensors," *Buildings*, vol. 13, no. 7, Jul. 2023, Art. no. 1684, https://doi.org/10.3390/buildings13071684.

[20] S. Tanwar, N. Patel, S. Patel, J. Patel, and I. Davidson, "Deep Learning-Based Cryptocurrency Price Prediction Scheme With Inter-Dependent Relations," *IEEE Access*, Vol. 9, Oct. 2021, https://doi.org/10.1109/ACCESS.2021.3117848.

[21] H. F. Nematallah, A. A. H. Sedky, and K. M. Mahar, "Bitcoin Price Trend Prediction Using Deep Neural Network," *Webology*, vol. 19, no. 3, pp. 2652–2655, 2022.

[22] F. Ferdiansyah, S. H. Othman, R. Z. M. Radzi, D. Stiawan, and T. Sutikno, "Hybrid gated recurrent unit bidirectional-long short-term memory model to improve cryptocurrency prediction accuracy," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 1, pp. 251–261, Mar. 2023, https://doi.org/10.11591/ijai.v12.i1.pp251-261.

[23] R. Murugesan, V. Shanmugaraja, and A. Vadivel, "Forecasting Bitcoin Price Using Interval Graph and ANN Model: A Novel Approach," *SN Computer Science*, vol. 3, no. 5, Aug. 2022, Art. no. 411, https://doi.org/10.1007/s42979-022-01291-x.

[24] C. Y. Kang, C. P. Lee, and K. M. Lim, "Cryptocurrency Price Prediction with Convolutional Neural Network and Stacked Gated Recurrent Unit," *Data*, vol. 7, no. 11, Nov. 2022, Art. no. 149, https://doi.org/10.3390/data7110149.

[25] S. A. Basher and P. Sadorsky, "Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility?," *Machine Learning with Applications*, vol. 9, Sep. 2022, Art. no. 100355, https://doi.org/10.1016/j.mlwa.2022.100355.

[26] P. L. Seabe, C. R. B. Moutsinga, and E. Pindza, "Forecasting Cryptocurrency Prices Using LSTM, GRU, and Bi-Directional LSTM: A Deep Learning Approach," *Fractal and Fractional*, vol. 7, no. 2, Feb. 2023, Art. no. 203, https://doi.org/10.3390/fractalfract7020203.

[27] K. Murray, A. Rossi, D. Carraro, and A. Visentin, "On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles," *Forecasting*, vol. 5, no. 1, pp. 196–209, Mar. 2023, https://doi.org/10.3390/forecast5010010.

[28] S. Boubaker, M. Benghanem, A. Mellit, A. Lefza, O. Kahouli, and L. Kolsi, "Deep Neural Networks for Predicting Solar Radiation at Hail Region, Saudi Arabia," *IEEE Access*, vol. 9, pp. 36719–36729, 2021, https://doi.org/10.1109/ACCESS.2021.3062205.

[29] J. Lago, F. De Ridder, and B. De Schutter, "Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms," *Applied Energy*, vol. 221, pp. 386–405, Jul. 2018, https://doi.org/10.1016/j.apenergy.2018.02.069.

[30] K. Tissaoui, "Forecasting implied volatility risk indexes: International evidence using Hammerstein-ARX approach," *International Review of Financial Analysis*, vol. 64, pp. 232–249, Jul. 2019, https://doi.org/10.1016/j.irfa.2019.06.001.

[31] Z. Ftiti, K. Tissaoui, and S. Boubaker, "On the relationship between oil and gas markets: a new forecasting framework based on a machine learning approach," *Annals of Operations Research*, vol. 313, no. 2, pp. 915–943, Jun. 2022, https://doi.org/10.1007/s10479-020-03652-2.

[32] G. Memarzadeh and F. Keynia, "Short-term electricity load and price forecasting by a new optimal LSTM-NN based prediction algorithm," *Electric Power Systems Research*, vol. 192, Mar. 2021, Art. no. 106995, https://doi.org/10.1016/j.epsr.2020.106995.

[33] O. M. Ahmed, L. M. Haji, A. M. Ahmed, and N. M. Salih, "Bitcoin Price Prediction using the Hybrid Convolutional Recurrent Model Architecture," *Engineering, Technology & Applied Science Research*, vol. 13, no. 5, pp. 11735–11738, Oct. 2023, https://doi.org/10.48084/etasr.6223.

[34] H. Rana, M. U. Farooq, A. K. Kazi, M. A. Baig, and M. A. Akhtar, "Prediction of Agricultural Commodity Prices using Big Data Framework," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12652–12658, Feb. 2024, https://doi.org/10.48084/etasr.6468.