Performance analysis of bitcoin forecasting using deep learning techniques

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ABSTRACT

The most popular cryptocurrency used worldwide is bitcoin. Many everyday folks and investors are now investing in bitcoin. However, it becomes quite difficult to evaluate or foresee the price of bitcoin. The price of bitcoin is extremely difficult to forecast due to its swings. By this point, machine learning has developed a number of models to examine the price behaviour of bitcoin using time series data. The digital money, a different type of payment developed utilising encryption methods, is difficult to forecast. By utilising encryption technology, cryptocurrencies may act as both a medium of exchange and a virtual accounting system. To estimate the values of a future time sequence, this work introduces a deep learning-based technique for time series forecasting that treats the current data as time series and extracts the key traits of the past. To overcome the shortcomings of conventional production forecasting, three algorithms-auto-regressive integrated moving averages (ARIMA), long-short-term memory (LSTM) network, and FB-prophet-were investigated and contrasted. We compared the models using historical bitcoin data of past eight years, from 2012 to 2020. The "FB-prophet" model, which is significant, catches variation that might draw attention and avert possible problems.

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1. INTRODUCTION

The cost-effectiveness of machine learning (ML) techniques enables us to maximise the value from enormous datasets produced by stock market price, financial exchange, and production. Second, operators are guided by ML algorithms that classify data, do linear regression, and use increasingly sophisticated neural network to examine the effect of geologic variety and operational factors [1], [2]. Given that deep learning and machine learning are frequently used synonymously, it is important to understand their differences. Neural network, deep learning, and machine learning are all branches of artificial intelligence [3], [4]. However, neural networks are the sub-field of deep learning, which itself is a field related to machine leaning. Some ML models outperform physical and empirical models in terms of prediction accuracy because they are more effective at identifying intricate and hidden patterns in data. Due to the past variations, time series forecasting is specifically used in bitcoin prediction. Supervised learning and unsupervised learning are the two types of utilised machine learning techniques in both production and exploration. For supervised learning, a labelled training dataset that includes both an output variable (xi) and one or more input characteristics (Xi) for each sample is required (yi). An algorithm initially learns how to translates these input-output pairs in order to predict the test (unseen) dataset with comparable properties. The supervised learning categories include: i) a regression issue, such as one using artificial neural network (ANN), linear regression, or support vector machine (SVM) regression. As opposed to independent values without temporal ordering, Time series machine learning generates a string of time-dependent values as its result, setting it apart from traditional regression-based ML as well as and ii) classification issues, including those involving logistic regression, SVM classification, random Forest classification, and gradient boosting machines (GBM) [5], [6]. In this paper the dataset is taken from github competition to forecast the model that is best for prediction. Here, the use of the prediction algorithms FB-prophet, long-short-term memory (LSTM), and auto-regressive integrated moving averages (ARIMA) demonstrates that FB-prophet and LSTM performs better than ARIMA.

2. RESEARCH METHOD

The implementation of financial operations has been significantly altered by the computerization of financial activities, connections through the internet, and support of associated software. The manner the activities are conducted has undergone a significant transformation [7]. The stock market is unpredictable and chaotic, making it difficult to anticipate even for those who have worked in the sector for a long time. Because of this, it is challenging to accurately estimate the market environment for the future. The key to improving data processing, analysis, and visualisation in the financial situation is to use machine learning and deep learning approaches. These algorithms typically analyse the data, find a pattern in the bitcoin prices from earlier years, extrapolate the trend, and provide the user with projected future bitcoin forecasting data. FB-prophet model can compete reasonably well with emerging forecasting techniques in short-term prediction [8]–[10]. So, first thing, what influences the bitcon (BTC) value is taken into account.

Two phases make up the project: the first entails analysing and recognising everyday patterns in the bitcoin market while obtaining information. The data sets are made up of several elements related to the bitcoin price and payment network throughout an eight-year period of daily recordings. The second entails properly predicting the direction of daily price movement using the facts at hand.

This study examines user feedback in online forums to forecast cryptocurrency transactions. The prices were expected to fluctuate at a modest cost. The technique employed authorised purchasing digital currencies and provided details on factors affecting user choices. Additionally, the simulated investment showed that the techniques used can be used when trading cryptocurrencies [11]. Number of issues discussed about the performance, comparisons of machine learning algorithms for cryptocurrency. Samin-Al-Wasee *et al.* [12], concentrations on the reasonable effectiveness of six cryptocurrencies' machine learning systems. First, six prominent cryptocurrencies have been discussed in the examination of cryptocurrencies: bitcoin, ethereum, litecoin, nem, ripple, and stellar. The long-short term memory networks were used to a significant financial market prediction assignment on the S&P 500, there is no statistical analysis are done in previous; here we discussed the comparisons along with the statistical analysis of each model [13].

2.1. Autoregressive integrated moving average

The autoregressive and moving average (ARMA) model is a crucial tool for time series analysis. The contributions of Yule, Slutsky, Walker, and Yaglom helped to develop the ideas of auto-regressive (AR) and moving average (MA) models. ARMA model is the foundation of ARIMA. The stagnant information before processing it. The ARIMA procedure's broad transfer function model. When additional time series are included as input variables for an ARIMA model, it is frequently referred to as an autoregressive integrated moving average with explanatory variable (ARIMAX) model [14], [15]. The ARIMAX model is referred to as dynamic regression by Jay *et al.* [16]. The identification, parameter estimation, and forecasting of univariate time series models may be done with a lot of flexibility using the ARIMA process. Since ARIMA produces more accurate findings than straight forecasting, it is a preferable strategy. However, if one cannot determine the effectiveness of the outcome, then just forecasting will be ineffective [17]–[19]. Thus, our current focus is on identifying the ARIMA model, LSTM, and FB-prophet that is both accurate and effective. It works best when the data exhibits a steady or consistent trend over time and has few outliers [20], [21]. According to (1), it contains the most recent observation of a time series of interest to signify the order of the AR and MA terms:

$$y_t=\alpha_0+\sum_{i=1}^{p}\alpha_i y_{t-1}+\sum_{j=0}^{q}\beta_j\varepsilon_{t-j} \tag{1}$$

where yt=the most recent observation of an interesting time series y_{t-1}(i=1, 2, …, p)=past annotations and ε_{t-j} (j=0, 1, 2, …, q)=random mistakes with a finite variance and a zero mean. The bayesian information criterion (BIC) rule chooses the order of the AR and MA terms, which are denoted by p and q, respectively.

2.2. Long short-term memory

The financial time series' one-step-ahead projection requires both the most recent and older data. The recurrent neural network (RNN) model offers benefit in trade with long-term reliance issues because of the self-feedback method of the hidden layer, however there are challenges in practical implementation. In 1997, sepp hochreiter and jurgen schmidhuber presented the LSTM model as a solution to the gradient disappearance of RNN problems. More recently, graves enhanced and popularised the LSTM model. A memory cell that holds data and is updated by three unique gates-the input gates, the forget gate, and the output gate-makes up an LSTM unit. Long-term and short-term memory is referred to as LSTM. It is a model or design that makes recurrent neural networks' memory larger. Recurrent neural networks often contain "short term memory" using persistent prior knowledge to inform the present neural network [22], [23]. According to Figure 1, it is a modified RNN designed to make it easier to remember previously stored information. The RNN vanishing gradient problem is resolved with it. In LSTM networks, layers connect memory blocks, which take the place of neurons [24]. Back propagation is used for training. Three gates are present in LSTM networks. A diagrammatic representation of the gates is shown Figure 1.

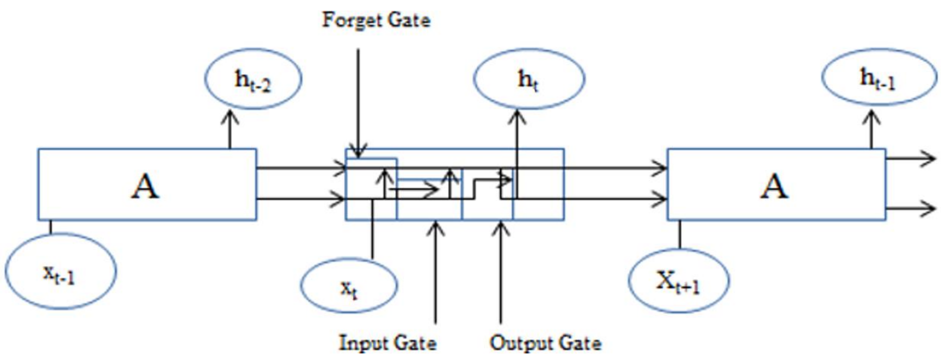

Figure 1. Structure of LSTM

2.3. FB-prophet

In order to accommodate non-linear patterns with periodicity that occur annually, monthly, daily, on weekends, and during vacations, FB-prophet utilises an additive model to forecast time series data. It works well with substantially annual time series and historical data from several seasons. Prophet is robust to incomplete information and swings in the trend and can generally tolerate outliers. The Facebook core data science team has just released prophet, a brand-new method for predicting time series data [25], [26]. It makes it possible to use Python 3 to scale up automated forecasting processes that are currently built in R. The research team at Facebook has developed prophet, a new library that makes predicting simpler to use. According to what i've read, it's uncommon to find analysts that can create high-quality predicting data [27]. This is one of the reasons Facebook's research team discovered an easy way to employ sophisticated principles for time series forecasting, and since this library leverages the scikit-learn API, Python users can readily relate to it. We can check out the prophet blog to learn more. The fundamental objective of the prophet team is to make it simpler for both specialists and non-experts to produce high-caliber forecasts that keep up with demand [28]. The Facebook prophet model, an open-source time-series database model generation method that incorporates some traditional concepts with some modern modifications. Particularly well suited for time series modelling. Exponential smoothing in the holt-winters technique uses the similar strategy of modelling seasonality as an additive component:

$$Y(t) = g(t) + s(t) + h(t) + e_t \tag{2}$$

according to (2), g(t) is the growth function which discovers changes in time series data, s(t) is the seasonality function, h(t) is the holiday information and e_t is the error rate. Prophet is attempting to appropriate for both linear and non-linear time functions as apparatuses while using time as a regressor.

3. PROPOSED MODEL

Figure 2, shows the lag plots of BTC dataset. A lag plot determines whether or not a set of data or a time series is random. On the lag plot, random data shouldn't show any discernible structure. The lag plot's non-random structure suggests that the original data are not random. Figure 3, depicts the full research's implementation procedure. The BTC dataset have eight number of columns they are; timestamp, open, high, low, close, volume, volume_(currency), and weighted_price. First of all, the timestamp is converted in to particular date and time format. Some null values are present in the dataset, these null values are imputed by using interpolation method. After filling values, the final dataset is prepared which is in the form of time series. The newly prepared dataset is now ready to feed by the models. The RMSE score for all three model is calculated and the comparison shows the efficient prediction model. Data cleansing, aggregation, and pricing computation are all done as part of data processing. The data is then prepared for time-series analysis and the prices of bitcoin are combined into a single dataframe. As demand and supply are taken into account when setting prices, it was noticed that accurate bitcoin values were not always simple to locate. Three of the largest exchanges for bitcoin include bitstamp, coinbase, and itbit. From these three, price information was retrieved, and on the basis of their "weighted price," all four pricing values were then integrated into a single dataframe [29]. After getting the final dataframe we run through our models then we evaluate the efficient model on the basis of their RMSE score.

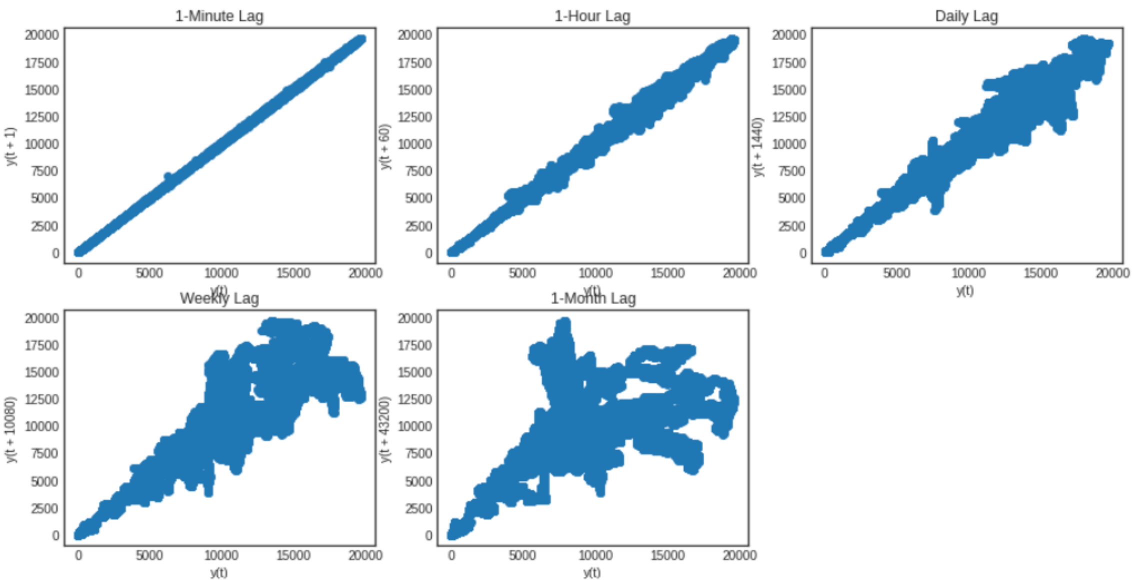

Figure 2. Lag plots of BTC data

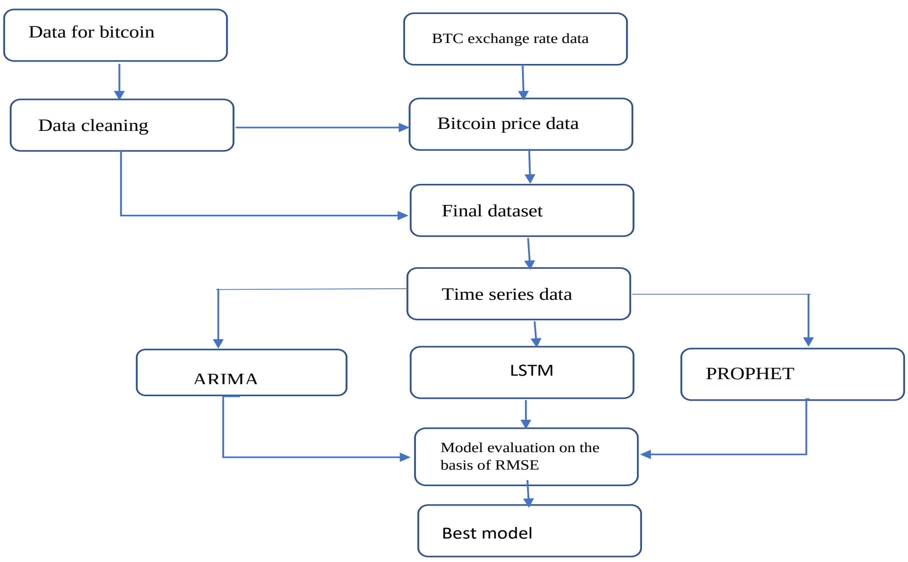

Figure 3. Complete workflow diagram

4. RESULTS AND DISCUSSION

This section illustrates the graphical representation of result and analysis on test dataset. Figure 4, shows the ARIMA predicted BTC price, where months and sample price rate taken in the x and y axis. Figure 5, depicts the LSTM predicted BTC price and similarly in Figure 6, shows the FB-prophet predicted BTC price. The test data is taken from the month of January 2020 to September 2020 in this dataset.

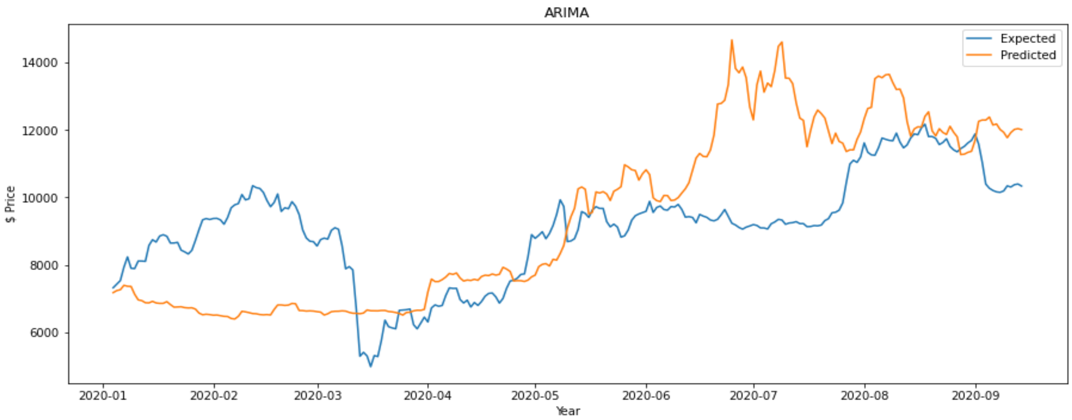

Figure 4. ARIMA predicted BTC price

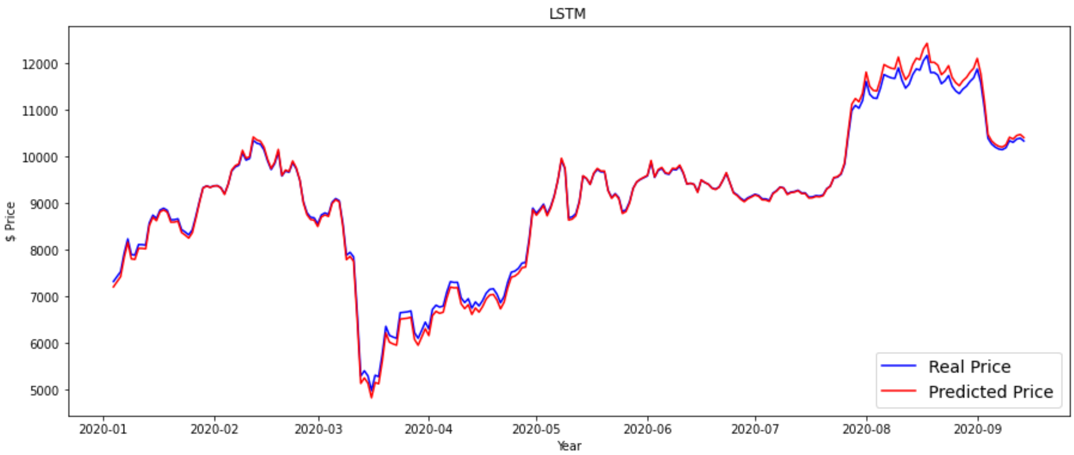

Figure 5. LSTM predicted BTC price

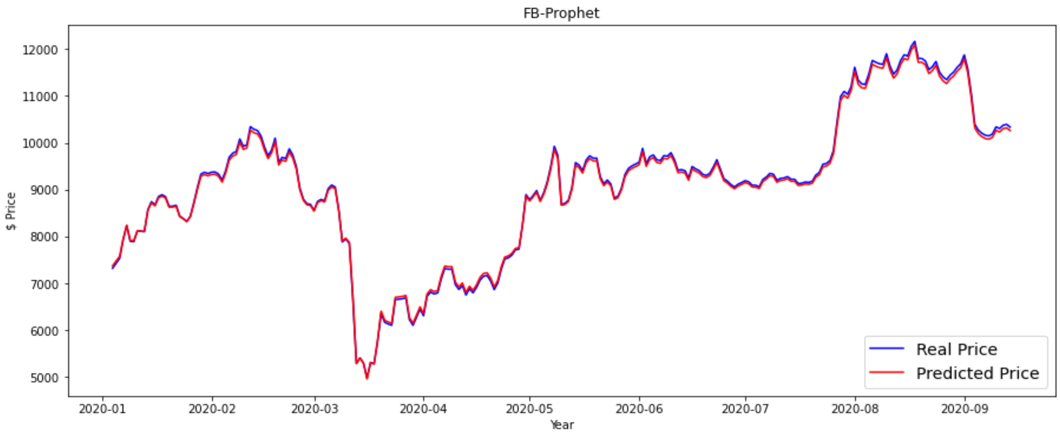

Figure 6. FB-prophet predicted BTC price

According to Table 1 we observed that the RMSE value of ARIMA is 2462.499, similarly the value for LSTM and FB-prophet is 421.292 and 322.599. This shows that the error in FB-prophet is minimal as compared to ARIMA and LSTM. We can conclude that FB-prophet outperformed both ARIMA and LSTM. Figure 7 shows the graphical representation of result with minimized RMSE value, here as per the result we getting the FB-prophet model is the most efficient model for forecasting the BTC price. Here in this Figure 7 deep learning models taken in the x-axis and the RMSE value of models taken in the y-axis.

Table 1. RMSE, MAE values of models

Model name	RMSE value	MAE value
ARIMA	2462.499	2126.062
LSTM	421.292	177486.955
FB-prophet	322.599	229.254

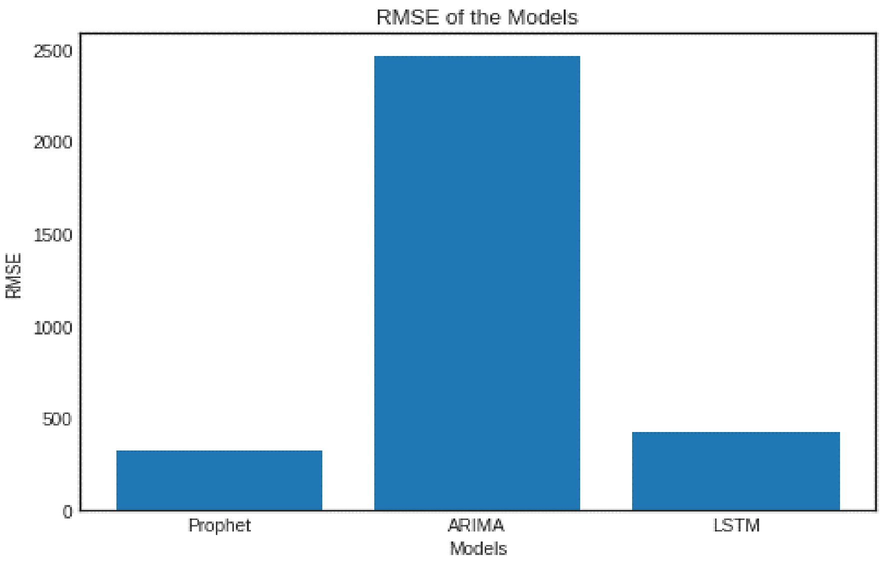

Figure 7. RMSE result of three models in bar diagram

5. CONCLUSION

The conclusion is based on the supplied dataset and the method. The share market is extremely volatile as a result of a number of reasons, including the present economic climate, the business environment, various physical and physiological elements, as well as prior patterns. However, the results may vary depending on the market, the time period under consideration, and the currencies taken into account for the forecast. The study's results are therefore arbitrary. Due to the production unpredictability in the past, we used time series forecasting. Through a self-learning process, deep learning algorithms are able to recognize and take advantage of the relationships and patterns present in a data set. Deep learning models can accurately represent this sort of data and provide a solid forecast by examining the relationships and hidden patterns within the data, unlike conventional methods. Different deep learning models are being used for multivariate time series analysis. When comparing the RMSE values of the three models, it was discovered that FB-prophet had the lowest RMSE value and that LSTM had the closest second place in terms of time series prediction, even if their operational methods are not entirely equivalent. The models might be trained for a short-term prediction and little dataset as a potential future extension. This analysis may be expanded further to forecast the performance of bitcoin using different machine learning models.

REFERENCES

[1] A. A. Adebiyi, A. O. Adewumi, and C. K. Ayo, "Stock price prediction using the ARIMA model," in *Proceedings - UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, UKSim 2014*, 2014, pp. 106–112, doi: 10.1109/UKSim.2014.67.

[2] A. M. Alonso and C. Garcia-Martos, "Time series analysis-forecasting with ARIMA models," *Universidad Carlos III de Madrid*, 2012.

[3] N. A. Hitam and A. R. Ismail, "Comparative performance of machine learning algorithms for cryptocurrency forecasting," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 11, no. 3, pp. 1121–1128, 2018, doi: 10.11591/ijeecs.v11.i3.pp1121-1128.

[4] M. Lukoševičius and H. Jaeger, "Reservoir computing approaches to recurrent neural network training," *Computer Science Review*, vol. 3, no. 3, pp. 127–149, Aug. 2009, doi: 10.1016/j.cosrev.2009.03.005.

[5] M. Geurts, G. E. P. Box, and G. M. Jenkins, "Time series analysis: forecasting and control," *Journal of Marketing Research*, vol. 14, no. 2. Holden-Day, San Francisco, p. 269, 1977, doi: 10.2307/3150485.

[6] Y. Ai *et al.*, "A deep learning approach on short-term spatiotemporal distribution forecasting of dockless bike-sharing system," *Neural Computing and Applications*, vol. 31, no. 5, pp. 1665–1677, May 2019, doi: 10.1007/s00521-018-3470-9.

[7] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," in *European Journal of Operational Research*, 2018, vol. 270, no. 2, pp. 654–669, doi: 10.1016/j.ejor.2017.11.054.

[8] K. Gajamannage, Y. Park, and D. I. Jayathilake, "Real-time forecasting of time series in financial markets using sequentially trained dual-LSTM," *Expert Systems with Applications*. E*xpert Systems with Applications*, p. 119879, 2023, doi: 10.1016/j.eswa.2023.119879.

[9] B. Petrevska, "Predicting tourism demand by A.R.I.M.A. models," in *Economic Research-Ekonomska Istrazivanja* , 2017, vol. 30, no. 1, pp. 939–950, doi: 10.1080/1331677X.2017.1314822.

[10] S. Agarwal and N. B. Muppalaneni, "Stock market price and cryptocurrency price prediction," in *IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics, ICDCECE 2022*, Apr. 2022, pp. 1–6, doi: 10.1109/ICDCECE53908.2022.9793088.

[11] S. Mehtab, J. Sen, and A. Dutta, "Stock price prediction using machine learning and LSTM-based deep learning models," in *Machine Learning and Metaheuristics Algorithms, and Applications: Second Symposium, SoMMA 2020*, 2021, vol. 1366, pp. 88–106, doi: 10.1007/978-981-16-0419-5_8.

[12] M. Samin-Al-Wasee, P. S. Kundu, I. Mahzabeen, T. Tamim, and G. R. Alam, "Time-series forecasting of ethereum price using long short-term memory (LSTM) networks," in *8th International Conference on Engineering and Emerging Technologies, ICEET 2022*, Oct. 2022, pp. 1–6, doi: 10.1109/ICEET56468.2022.10007377.

[13] R. K. Rathore *et al.*, "Real-world model for bitcoin price prediction," *Information Processing and Management*, vol. 59, no. 4, 2022, doi: 10.1016/j.ipm.2022.102968.

[14] M. Iqbal, M. Iqbal, F. Jaskani, K. Iqbal, and A. Hassan, "Time-series prediction of cryptocurrency market using machine learning techniques," *EAI Endorsed Transactions on Creative Technologies*, vol. 8, no. 28, p. 170286, 2021, doi: 10.4108/eai.7-7-2021.170286.

[15] I. Sadia, A. Mahmood, L. B. M. Kiah, and S. R. Azzuhri, "Analysis and forecasting of blockchain-based cryptocurrencies and performance evaluation of TBATS, NNAR and ARIMA," in *4th IEEE International Conference on Artificial Intelligence in Engineering and Technology, IICAIET 2022*, Sep. 2022, pp. 1–6, doi: 10.1109/IICAIET55139.2022.9936798.

[16] P. Jay, V. Kalariya, P. Parmar, S. Tanwar, N. Kumar, and M. Alazab, "Stochastic neural networks for cryptocurrency price prediction," *IEEE Access*, vol. 8, pp. 82804–82818, 2020, doi: 10.1109/ACCESS.2020.2990659.

[17] H. I. Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P. A. Muller, "Deep learning for time series classification: a review," *Data Mining and Knowledge Discovery*, vol. 33, no. 4, pp. 917–963, Jul. 2019, doi: 10.1007/s10618-019-00619-1.

[18] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[19] K. Songmuang, L. Thungwha, and C. Tanaram, "The forecasting of cryptocurrency price by correlation and regression analysis," *Kasem Bundit Journal*, vol. 19, no. June, pp. 287–296, 2018.

[20] G. Tian, Q. Wang, Y. Zhao, L. Guo, Z. Sun, and L. Lv, "Smart contract classification with a Bi-LSTM based approach," *IEEE Access*, vol. 8, pp. 43806–43816, 2020, doi: 10.1109/ACCESS.2020.2977362.

[21] S. G. P. Prusty and S. Prusty, "Time series analysis of SAR-Cov-2 Virus in India using Facebook's prophet," in *Meta Heuristic Techniques in Software Engineering and Its Applications: METASOFT*, 2022, pp. 72–81, doi: 10.1007/978-3-031-11713-8_8.

[22] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: continual prediction with LSTM," *Neural Computation*, vol. 12, no. 10, pp. 2451–2471, Oct. 2000, doi: 10.1162/089976600300015015.

[23] R. Khaldi, A. E. Afia, and R. Chiheb, "Forecasting of BTC volatility: comparative study between parametric and nonparametric models," *Progress in Artificial Intelligence*, vol. 8, no. 4, pp. 511–523, 2019, doi: 10.1007/s13748-019-00196-w.

[24] I. Yenidogan, A. Cayir, O. Kozan, T. Dag, and C. Arslan, "Bitcoin forecasting using ARIMA and PROPHET," in *UBMK 2018-3rd International Conference on Computer Science and Engineering*, 2018, pp. 621–624, doi: 10.1109/UBMK.2018.8566476.

[25] X. Sun, M. Liu, and Z. Sima, "A novel cryptocurrency price trend forecasting model based on LightGBM," *Finance Research Letters*, vol. 32, p. 101084, 2020, doi: 10.1016/j.frl.2018.12.032.

[26] V. Derbentsev, A. Matviychuk, and V. N. Soloviev, "Forecasting of cryptocurrency prices using machine learning," in *Advanced Studies of Financial Technologies and Cryptocurrency Markets*, 2020, pp. 211–231, doi: 10.1007/978-981-15-4498-9_12.

[27] S. Prusty, S. Patnaik, and S. K. Dash, "Comparative analysis and prediction of coronary heart disease," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 27, no. 2, pp. 944–953, 2022, doi: 10.11591/ijeecs.v27.i2.pp944-953.

[28] D. Stosic, D. Stosic, T. B. Ludermir, and T. Stosic, "Collective behavior of cryptocurrency price changes," *Physica A: Statistical Mechanics and its Applications*, vol. 507, pp. 499–509, Oct. 2018, doi: 10.1016/j.physa.2018.05.050.

[29] T. R. Li, A. S. Chamrajnagar, X. R. Fong, N. R. Rizik, and F. Fu, "Sentiment-based prediction of alternative cryptocurrency price fluctuations using gradient boosting tree model," *Frontiers in Physics*, vol. 7, Jul. 2019, doi: 10.3389/fphy.2019.00098.

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