

# The prediction of Bitcoin price through gold price using long short-term memory model

Jae Won Choi<sup>1</sup>, Young Keun Choi<sup>2</sup>

<sup>1</sup>Department of Computer Science, University of Texas at Dallas, Richardson, USA

<sup>2</sup>Division of Business Administration, Sangmyung University, Seoul, Republic of Korea

## Article Info

### Article history:

Received Jan 27, 2023

Revised May 19, 2023

Accepted Jun 30, 2023

### Keywords:

Bitcoin price prediction

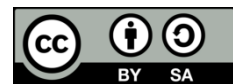
Cryptocurrency

Long short-term memory

## ABSTRACT

The majority of research on predicting the price of Bitcoin employs technical methods to enhance long short-term memory models' effectiveness. Although some studies employ different machine learning techniques, such as economic or technical indicators, their precision is inadequate. Thus, this research aims to introduce a model that predicts the price of Bitcoin by utilizing the long short-term memory (LSTM) technique and incorporating gold's economic and technical data as features. The research collected gold and Bitcoin price data from FinanceDataReader for around seven years, from January 1, 2016, to January 22, 2023, consisting of six categories: date, open, high, low, close, volume, and change (based on dollars). The normalized closing price data was trained for 50 epochs, resulting in the loss value reaching close to zero. The model's accuracy was measured by mean squared error, resulting in a score of 0.0004. This study's importance is two-fold: firstly, it can provide cryptocurrency-related businesses with more accurate predictions and improved risk management indicators. Secondly, incorporating economic metrics can address the limitations of overfitting and a single model's poor performance.

*This is an open access article under the [CC BY-SA](#) license.*



## Corresponding Author:

Youngkeun Choi

Division of Business Administration, Sangmyung University

20, Hongjimun 2-gil, Jongno-gu, Seoul 110-743, Korea

E-mail: penking1@smu.ac.kr

## 1. INTRODUCTION

According to scholarly research, blockchain technology is widely acknowledged as a pivotal innovation that is expected to greatly influence the fourth industrial revolution, along with other cutting-edge technologies [1]. The increasing adoption of blockchain technology and the growing interest in cryptocurrency highlight its popularity. The fundamental concept of blockchain technology is decentralization, which ensures transaction security through encryption for information shared among a large network of participants [2]. It consists of a public block that allows open participation and access to information, as well as a private blockchain managed by a central entity.

Cryptocurrencies are a type of payment that is received by participating in public events on blockchain networks. As blockchain technology evolves, the number of cryptocurrency transactions continues to grow [3]. With the rising trading volume of prominent cryptocurrencies, there is growing interest among researchers in predicting cryptocurrency prices using text mining and deep learning methods. Previous studies have primarily focused on either prediction based on text mining, which involves analyzing sentiments from cryptocurrency-related news or social media, or prediction based on machine learning/deep learning techniques [4].

The limitations of the natural language processing technology utilized in this research are evident as it struggles to accurately capture the meaning and context of specialized terminologies unique to the cryptocurrency market. Several studies have been conducted to evaluate the effectiveness of different machine learning and deep learning models, revealing research accuracy rates ranging from 40% to 70%, indicating the need for improved performance [5], [6]. Additionally, the long-term, time-based prediction nature of this study presents challenges in applying it to the highly liquid cryptocurrency market.

When utilizing machine learning algorithms for Bitcoin price prediction, there may be a question regarding which characteristics ought to be taken into account. While prior investigations have examined techniques for selecting [7] and measuring [8] features, these studies have mainly relied on domain expertise [9] and may lack a thorough consideration of all feature dimensions. To tackle this concern, this study incorporates current empirical research on factors that impact the price of Bitcoin from scholars with a profound comprehension of the subject matter.

Economists have noted similarities between Bitcoin and gold in terms of scarcity, high extraction costs, and independence from government control or nationality. Bitcoin may encounter comparable challenges to gold, which functioned as a tool of transaction during the gold era but was ultimately forsaken because of liquidity worries [10], if its user population persists in expanding. Despite their differences, both assets are valuable and can be used interchangeably. However, it appears unlikely that the Bitcoin price of 240.5 USD as of June 2015 can be rationalized based on logical user behavior and intrinsic value [11].

This research focuses on the gold market and the Bitcoin market, pinpointing pertinent characteristics. The development of an accurate machine learning method for predicting Bitcoin price is crucial due to the absence of seasonality in Bitcoin and its suitability for machine learning models. A popular algorithm used in previous studies is the long short-term memory model. However, previous research has not adequately considered data frequency or sample size, which can result in errors such as overfitting. To avoid these complications, it is important to carefully consider the structures of data with different frequencies. As such, this study aims to determine whether economic and technological factors that impact gold prices can be used to accurately predict Bitcoin prices.

## 2. RELATED WORK

Previously, scholars have investigated diverse methods for forecasting the values of cryptocurrencies, which are classified into three main areas depending on how data is employed. These categories include studies that utilize i) text mining, ii) machine learning/deep learning, and iii) a combination of text mining and machine learning/deep learning. Studies that utilized text mining primarily extracted data from social media and articles, employing sentiment analysis to forecast cryptocurrency prices [7]. However, these studies encountered methodological limitations as information such as the number of posts or numerical trends proved to be more valuable than the text data itself. Additionally, concerns arose regarding the reliability of text interpretation and the inconsistency among individual responses to text data, posing challenges for generalization [4].

Furthermore, prior research on forecasting cryptocurrency values with machine learning analysis involved the comparison of various machine learning or deep learning models [6], [9]. A notable research area focuses on utilizing deep learning models to forecast time-series characteristics and nonlinear volatility in financial markets, enabling accurate predictions of intricate patterns and flows that are inherently challenging to comprehend [12], [13]. In their research, Greaves and Au [13] utilized machine learning techniques to make predictions about trends in cryptocurrency price movements. Similarly, McNally *et al.* [9] and Samaddar *et al.* [6] attempted to forecast cryptocurrency prices with long short-term memory (LSTM). However, previous studies have primarily concentrated on long-term price predictions, achieving accuracy rates ranging from 40% to 70% in forecasting price fluctuations.

Lastly, there are scholarly investigations that employ a combination of text mining and machine learning/deep learning analyses [5]. These studies primarily center on conducting text-mining analyses, and subsequently utilizing machine-learning analyses based on the obtained results. Nevertheless, these studies are constrained by conducting separate comparative analyses of the analysis outcomes, rather than integrating the analysis techniques. Additionally, there is a limitation in that the prediction of cryptocurrency prices primarily relies on machine learning/deep learning analyses, rather than text mining analyses [14].

Currently, there is insufficient empirical evidence to support the effectiveness of machine learning algorithms in accurately predicting the Bitcoin price. The existing research is also limited in scope. Shah and Zhang [15] employed a Bayesian regression model referred to as the "latent source model" suggested by Chen *et al.* [16], which utilizes binary classification to forecast changes in Bitcoin prices. In their study, Greaves *et al.* [13] used machine learning to examine the features' impacts on Bitcoin prices and were able to achieve an accuracy rate of around 55%. Madan *et al.* [17] utilized machine learning for predicting Bitcoin prices and obtained a daily price accuracy rate of 98.7% and a high-frequency price accuracy rate of 50% to

55%. McNally *et al.* [9] compared and analyzed bitcoin price predictions with various methodologies, and the results indicated that LSTM exhibited the highest accuracy rate at 52%.

LSTM has shown its effectiveness in predicting the highly unpredictable price of Bitcoin [18]–[20]. However, previous studies on Bitcoin price prediction have mostly concentrated on improving LSTM models from a technical perspective [21], [22]. On the other hand, studies that have used non-LSTM machine learning techniques have incorporated economic or technical features, but their accuracy has been low [23]–[25]. Therefore, this research aims to propose a model that combines the LSTM approach with the economic and technical characteristics of gold as features to forecast Bitcoin price.

### 3. METHODOLOGY

#### 3.1. Sample

The data for this research was obtained from FinanceDataReader, which included gold and Bitcoin price data spanning a period of approximately 7 years, from January 1, 2016, to January 22, 2023. We collected a total of 2,577 days of Bitcoin price data, which comprised six categories: date, open, high, low, close, volume, and change (in dollars). The data was stored at a 24-hour interval, making it suitable for short-term price prediction (24 hours ahead) in this study. The distribution of gold prices is depicted in Figure 1, while Figure 2 displays the distribution of Bitcoin prices.

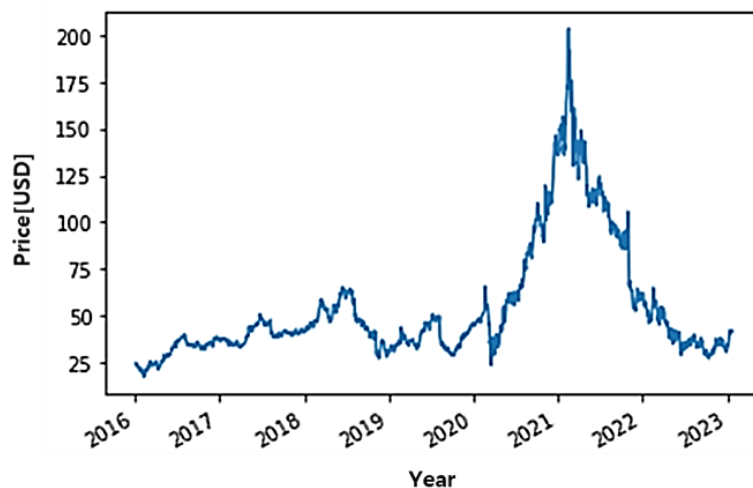


Figure 1. Shows gold price distribution

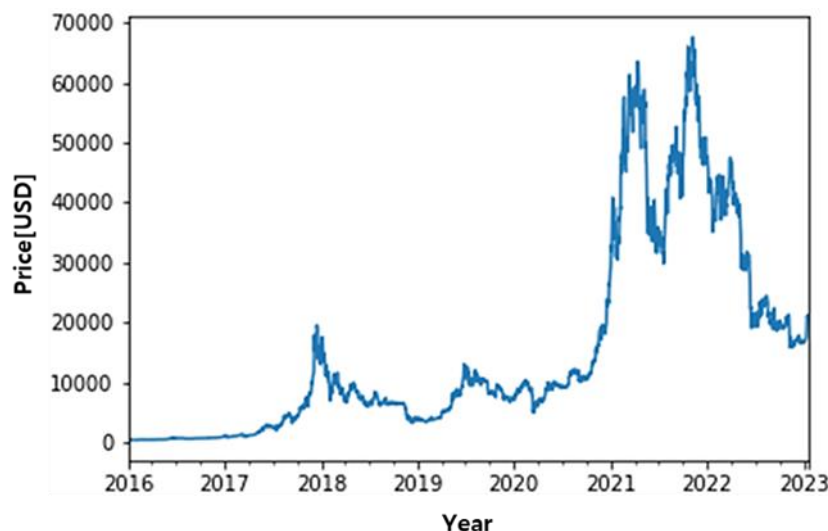


Figure 2. Shows Bitcoin price distributio

### 3.2. Data preprocessing

This study aims to forecast the final Bitcoin price by employing diverse variables, such as the initial price, peak price, bottom price, trading volume, and fluctuations of both Bitcoin and gold, through a comprehensive analysis. Python programming language was utilized for data pre-processing, which encompassed four main steps: i) converting raw data into a data frame, ii) refining the data, iii) normalizing the data, and iv) segmenting the data. Initially, the data sequence, which consisted of daily data, was set to a length of 30 and restructured into a data frame matrix where each unit represented 30 days. Subsequently, in the data refinement process, 27 missing values (1.04% of the total) such as null values or data marked as 0 were replaced with the mean value to address missing data. Next, data normalization was performed to scale all values of input within the range of 0 and 1. Finally, we divided the data into training data (7 parts) and test data (3 parts) in a 7:3 ratio for model development and evaluation. However, considering that the data was in a time series format, the most recent data was selected as the test data to account for temporal order. Moreover, hyper-parameters were further divided into training and validation sets at an 8:2 ratio, from the 7 parts of training data that was split for model optimization.

### 3.3. Price prediction with LSTM model

When examining financial time-series information, recurrent neural network (RNN) are capable of capturing sequential patterns. However, they encounter obstacles such as gradient vanishing or exploding, and inadequate integration of past data. Nonetheless, a specialized RNN variant known as LSTM excels at handling long-term dependencies in time-series data, which makes it a more effective model than conventional RNNs.

The LSTM network design, as illustrated in Figure 3, consists of memory blocks that consist of a memory cell and three gates. The gate structures have the crucial function of regulating the state of the memory cell. To be specific, the forget gate plays a role in selecting the historical information to be discarded from the memory cell state, while the input gate governs the effect of the current input data on the memory cell state. Finally, the output gate determines the output information of the memory cell. In summary, these gates are responsible for managing and controlling various aspects of the memory cell state.

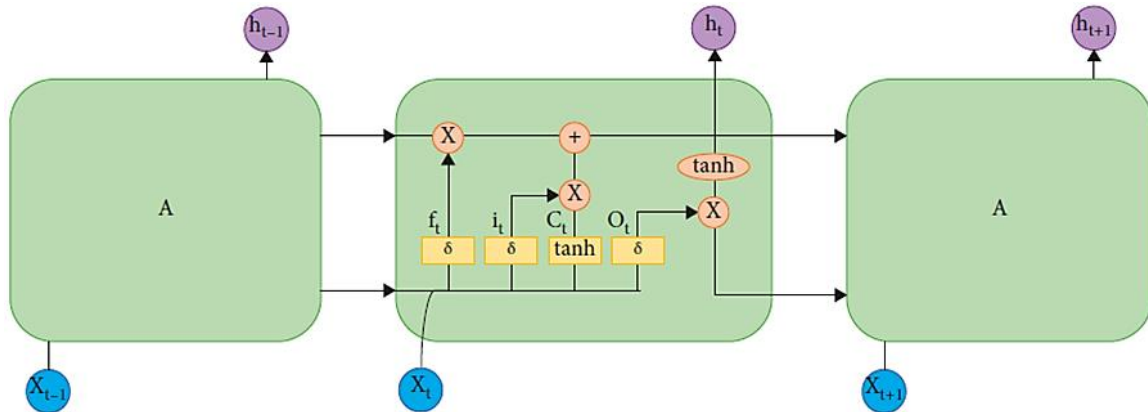


Figure 3. Shows LSTM network structure

Firstly, the data must be erased from the cell. And, it is identified based on the forget gate ( $f_t$ ) of the (1). It is outlined:

$$f_t = \sigma(bf + Wf x_t + Uf h_{t-1}) \quad (1)$$

The sigmoid function  $\sigma$  is utilized for computing the preserved data in the neural network. The input vector at the current time step is referred to as  $x_t$ , and the hidden layer vector is represented by  $h_t$ . In the architecture of the neural network, the forget gate consists of bias ( $bf$ ), input weight ( $x_t$ ), and loop weight ( $h_t$ ).

Afterward, the information state is updated within the cell. As mentioned in (2), the external input gate ( $i_t$ ) is governed by the sigmoid activation function. It is outlined below:

$$i_t = \sigma(bg + Wg x_t + Ug h_{t-1}) \quad (2)$$

In (3) is used to update the cell state ( $C_t$ ) by incorporating  $C_{t-1}$  as the input.

$$C_t = f_t * C_{t-1} + g_t * \tanh(bc + W_{cxt} + U_{cht} - 1) \quad (3)$$

$C_t$  denotes the status of the memory cell at a specific moment,  $t$ .

Lastly, the output gate ( $O_t$ ) of (4) regulates the information output in the following manner:

$$h_t = (O_t)\tanh(C_t) \quad (4)$$

$$O_t = \sigma(b_o + W_o x_t + U_o h_{t-1} - 1) \quad (5)$$

To evaluate the model precision, mean squared error (MSE) was utilized as a typical loss function for neural network models engaged in regression tasks. The MSE measures the mean value of the squared discrepancies between the predicted values and the actual values. The reason for selecting MSE in this research is manifold. Firstly, MSE is a differentiable function, which implies that it can be applied in the backpropagation algorithm for updating the model's weights. Secondly, MSE accounts for the magnitude of the error, as larger errors are squared, emphasizing their impact and aiding in reducing prediction errors during model training. Thirdly, MSE is robust to outliers, making it suitable for evaluating model performance even in the presence of data outliers. The calculation of MSE was performed as shown in (6), where  $y_k$  represents the predicted value and  $t_k$  represents the actual value.

$$MSE = \frac{1}{n} \sum_k (y_k - t_k)^2 \quad (6)$$

where the variable " $n$ " denotes the data size.

### 3.4. Train and test the model

In this research, the LSTM model was constructed and then the hyperparameter optimization process was performed to enhance its performance. The primary optimization process involved exploring the number of neurons and epochs. The LSTM model consists of two layers, each with a variable number of neurons denoted by ' $n$ '. The study involved conducting experiments where the number of neurons was manipulated, ranging from 16, 32, 64, 128, to 200, and the number of epochs varied between 10, 30, 50, and 100. It was found that if the number of epochs is too small, the model does not train effectively, and if it is too large, overfitting issues may arise. As a result, the optimal combination of hyperparameters was determined to be 32 neurons and 50 epochs, yielding the best prediction results for the verification data.

In the secondary optimization process, the optimal window size and activation function were determined. This process was conducted with the number of neurons and epochs fixed at 32 and 50, respectively. The window size refers to the size of the previous dataset used for model learning, and experiments were performed with window sizes of 10, 7, 5, and 3. The activation function, which converts input values to output values in the hidden layers of the LSTM, was also optimized. Recurrent activation, a commonly used function in time-series analysis, was considered during the analysis.

The sigmoid function was utilized in its original form, while the gate function was compared and analyzed against four other functions, namely tanh, relu, linear, and softmax. Through secondary analysis, it was determined that the combination of the tanh function as the gate function with a window size of 7 yielded the best prediction results for the verification data. Further hyperparameter selection was performed during the first and second optimization processes. In this study, a dropout ratio of 0.25 was designated to randomly disconnect some of the connections between neurons to prevent overfitting. The batch size, which determines the amount of data passed to the next network after learning, was set to 2 to manage computer memory usage. Sequence length and output dimension were set to 30 days as units of measurement. Adam optimizer and MSE were used as the optimizer and loss function, respectively.

## 4. RESULTS

The closing price data was normalized and trained for 50 epochs in this research paper. The loss value, as depicted in Figure 4, converged close to 0 after learning. Although there were instances where the validation-set loss temporarily spiked due to sudden fluctuations in stock prices, it generally converged to 0. The outcomes of testing the trained model with test data are illustrated in Figure 5. Before output, the test results underwent inverse normalization. The model accuracy, as measured by MSE, yielded a result of 0.0004. Through testing with the trained model, it was confirmed that the actual value trend was accurately followed, as demonstrated in Figure 5.

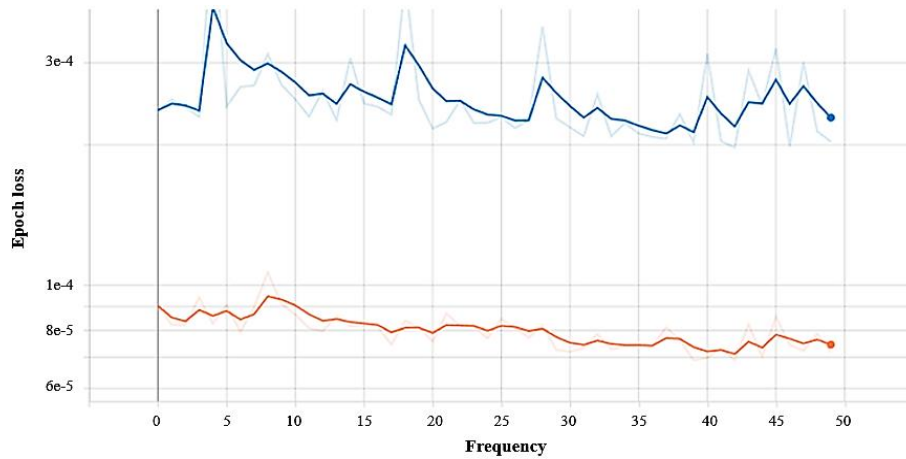


Figure 4. Shows learning loss value

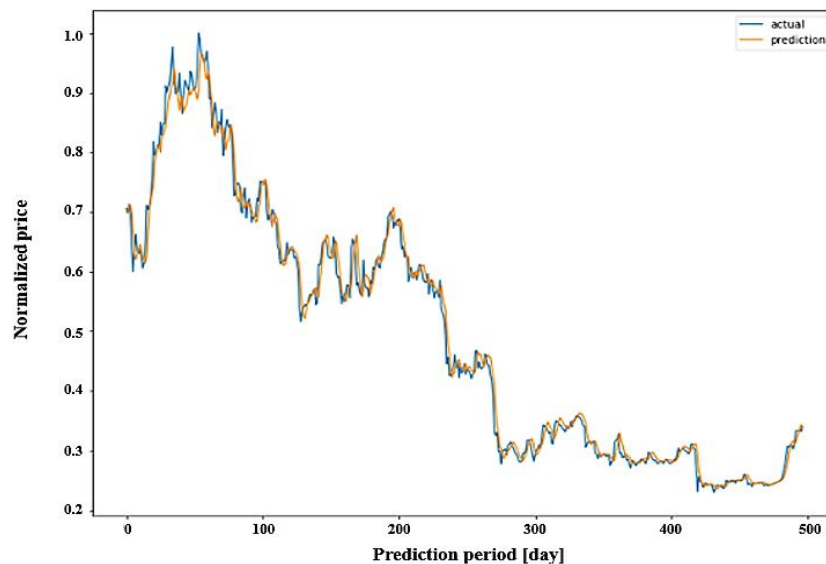


Figure 5. Shows prediction result

## 5. CONCLUSION

Currently, the cryptocurrency market is experiencing significant investment due to the heightened interest in blockchain technology. However, there is a research gap when it comes to predicting cryptocurrency prices. Previous studies have attempted to forecast prices using text mining and machine/deep learning techniques, but there were limitations. Text mining studies focused on sentiment analysis of articles related to cryptocurrencies, but factors such as the number of posts or numerical trends had a more significant impact on price prediction than sentiment analysis. Machine/deep learning studies were focused on improving artificial intelligence techniques, necessitating a fresh approach. To address this research gap, this study has developed an LSTM model that predicts the price of Bitcoin based on gold prices. The model achieved an exceptionally low loss value and an MSE value of 0.0004 for Bitcoin closing price predictions. The results depicted in Figure 5 of this study reveal that the predicted value lags behind the actual value at the turning point. This phenomenon could be attributed to several factors. Firstly, data can change dramatically at tipping points, leading to different patterns than before, which can affect the predictive model. For instance, at a turning point, market conditions or investor behavior patterns may emerge differently. Secondly, turning points tend to introduce increased uncertainty, as unpredictable variables may surface. This uncertainty can reduce the accuracy of predictive models. Lastly, existing data patterns may not hold valid at a turning point. For example, predictive models based on past patterns may yield different outcomes at turning points, resulting in decreased accuracy.

Therefore, predictive models are often less precise during tipping points. To enhance predictions during tipping points, adjustments, and refinements must be made to the model to account for data and uncertainties specific to those critical junctures. An analysis reveals that Bitcoin shares similarities with both gold and the dollar. Bitcoin can function as a means of transaction, and its worth is largely affected by the federal funds rate, indicating its similarity to a currency. Nevertheless, because Bitcoin has a decentralized structure and lacks significant regulation, it cannot be considered a mere replica of traditional currencies. Bitcoin shares many similarities with gold, such as its responsiveness to similar factors, its ability to hedge against risks, and its symmetric reactions to good and bad news. Nevertheless, Bitcoin's trading frequency is likely higher, and it responds more swiftly to market sentiment. Bitcoin, being decentralized and with a relatively small market size, can be classified as situated between a currency and a commodity. However, this does not diminish the value of Bitcoin as an asset in the market. In contrast, integrating Bitcoin into the management of investment portfolios and analysis of the market can offer a more holistic viewpoint, resulting in informed choices and an extra instrument for hedging. Moreover, risk-averse investors can utilize Bitcoin as a tool to prepare for unfavorable news. By combining the benefits of a pure store of value represented by gold and the merit of a pure tool of the transaction represented by the dollar, Bitcoin has positioned itself as a hybrid in the market. This observation implies that Bitcoin can offer the advantages of both currencies and commodities in the financial industry, which can be beneficial for managing portfolios, analyzing risks, and gauging market sentiment. The significance of this research lies in its potential to provide cryptocurrency-related companies with more advanced forecasting and risk management indicators. Currently, major services like Facebook have announced their intentions to issue and use cryptocurrencies, while other services that utilize artificial intelligence technology to analyze historical cryptocurrency price data and make price predictions are also emerging. Many researchers are also working on developing novel algorithms for cryptocurrency price prediction, utilizing various combinations of machine-learning models. However, in this study, we have improved upon existing algorithms by optimizing hyperparameters based on LSTM, resulting in a model with superior performance. Economic metrics were employed to address the limitations of a single model and its propensity to overfit. As a result, the accuracy of the predictions in this study exceeds that of prior research that solely relied on a single machine-learning model for forecasting cryptocurrency prices, which is a notable achievement.

## REFERENCES




- [1] A. A., Almarshadi, S., Shaath, and A., "The fourth industrial revolution and its impact on the hospitality industry," *Journal of Tourism and Hospitality Management*, vol. 10, no. 1, pp. 1–15, 2022.
- [2] L. Ante, I. Fiedler, J. M. Willruth, and F. Steinmetz, "A systematic literature review of empirical research on stablecoins," *FinTech*, vol. 2, no. 1, pp. 34–47, 2023, doi: 10.3390/fintech2010003.
- [3] F. H. L. Chong, "Enhancing trust through digital Islamic finance and blockchain technology," *Qualitative Research in Financial Markets*, vol. 13, no. 3, pp. 328–341, Jun. 2021, doi: 10.1108/QRFM-05-2020-0076.
- [4] S. Oikonomopoulos, K. Tzafilkou, D. Karapiperis, and V. Verykios, "Cryptocurrency price prediction using social media sentiment analysis," *13th International Conference on Information, Intelligence, Systems and Applications, IISA 2022*, 2022, doi: 10.1109/IISA56318.2022.9904351.
- [5] A. M. Rather, "A new method of ensemble learning: case of cryptocurrency price prediction," *Knowledge and Information Systems*, vol. 65, no. 3, pp. 1179–1197, 2023, doi: 10.1007/s10115-022-01796-0.
- [6] M. Samaddar, R. Roy, S. De, and R. Karmakar, "A comparative study of different machine learning algorithms on Bitcoin value prediction," *Proceedings of the 2021 1st International Conference on Advances in Electrical, Computing, Communications and Sustainable Technologies, ICAECT 2021*, 2021, doi: 10.1109/ICAECT49130.2021.9392629.
- [7] S. Rouhani and E. Abedin, "Crypto-currencies narrated on tweets: a sentiment analysis approach," *International Journal of Ethics and Systems*, vol. 36, no. 1, pp. 58–72, 2020, doi: 10.1108/IJOES-12-2018-0185.
- [8] L. M. Abualigah, A. T. Khader, E. S. Hanandeh, and A. H. Gandomi, "A novel hybridization strategy for krill herd algorithm applied to clustering techniques," *Applied Soft Computing*, vol. 60, no. 1, pp. 423–435, Nov. 2017, doi: 10.1016/j.asoc.2017.06.059.
- [9] S. McNally, J. Roche, and S. Caton, "Predicting the price of Bitcoin using machine learning," *Proceedings - 26th Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, PDP 2018*, pp. 339–343, 2018, doi: 10.1109/PDP2018.2018.00060.
- [10] A. Alaoui Mdaghri, A. Raghibi, C. N. Thanh, and L. Oubdi, "Stock market liquidity, the great lockdown and the COVID-19 global pandemic nexus in MENA countries," *Review of Behavioral Finance*, vol. 13, no. 1, pp. 51–68, 2021, doi: 10.1108/RBF-06-2020-0132.
- [11] E. Pagnotta and A. Buraschi, "An equilibrium valuation of bitcoin and decentralized network assets," *SSRN Electronic Journal*, 2018, doi: 10.2139/ssrn.3142022.
- [12] K. Khare, O. Darekar, P. Gupta, and V. Z. Attar, "Short term stock price prediction using deep learning," *RTEICT 2017 - 2nd IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, Proceedings*, vol. 2018-January, pp. 482–486, 2017, doi: 10.1109/RTEICT.2017.8256643.
- [13] B. Greaves, Alex and Au, "Using the bitcoin transaction graph to predict the price of bitcoin," *Quoted*, vol. 3, p. 22, 2015, [Online]. Available: [http://snap.stanford.edu/class/cs224w-2015/projects\\_2015/Using\\_the\\_Bitcoin\\_Transaction\\_Graph\\_to\\_Predict\\_the\\_Price\\_of\\_Bitcoin.pdf](http://snap.stanford.edu/class/cs224w-2015/projects_2015/Using_the_Bitcoin_Transaction_Graph_to_Predict_the_Price_of_Bitcoin.pdf).
- [14] A. Jain, S. Tripathi, H. Dhardwivedi, and P. Saxena, "Forecasting price of cryptocurrencies using tweets sentiment analysis," *2018 11th International Conference on Contemporary Computing, IC3 2018*, 2018, doi: 10.1109/IC3.2018.8530659.
- [15] D. Shah and K. Zhang, "Bayesian regression and Bitcoin," *2014 52nd Annual Allerton Conference on Communication, Control, and Computing, Allerton 2014*, pp. 409–414, 2014, doi: 10.1109/ALLERTON.2014.7028484.






- [16] G. H. Chen, S. Nikolov, and D. Shah, "A latent source model for nonparametric time series classification," *Advances in Neural Information Processing Systems*, 2013.
- [17] I. Madan, S. Saluja, A. Zhao, I. Madan, S. Saluja, and A. Zhao, "Automated Bitcoin trading via machine learning algorithms. Available via DIALOG," *The Weizmann Institute of Science*, pp. 1–5, 2015, [Online]. Available: [http://cs229.stanford.edu/proj2014/Isaac Madan, Shaurya Saluja, Aojia Zhao,Automated Bitcoin Trading via Machine Learning Algorithms.pdf%0Ahttps://www.semanticscholar.org/paper/Automated-Bitcoin-Trading-via-Machine-Learning-Madan/e0653631b4a476abf5276a264](http://cs229.stanford.edu/proj2014/Isaac%20Madan,%20Shaurya%20Saluja,%20Aojia%20Zhao,Automated%20Bitcoin%20Trading%20via%20Machine%20Learning%20Algorithms.pdf%0Ahttps://www.semanticscholar.org/paper/Automated-Bitcoin-Trading-via-Machine-Learning-Madan/e0653631b4a476abf5276a264).
- [18] X. Lu, C. Liu, K. K. Lai, and H. Cui, "Risk measurement in Bitcoin market by fusing LSTM with the joint-regression-combined forecasting model," *Kybernetes*, 2021, doi: 10.1108/K-07-2021-0620.
- [19] V. Ramos, W. Yamaka, B. Alorda, and S. Sriboonchitta, "High-frequency forecasting from mobile devices' bigdata: an application to tourism destinations' crowdedness," *International Journal of Contemporary Hospitality Management*, vol. 33, no. 6, pp. 1977–2000, 2021, doi: 10.1108/IJCHM-10-2020-1170.
- [20] X. Tian, J. S. He, and M. Han, "Data-driven approaches in FinTech: a survey," *Information Discovery and Delivery*, vol. 49, no. 2, pp. 123–135, 2021, doi: 10.1108/IDD-06-2020-0062.
- [21] Z. H. Fang and C. C. Chen, "A collaborative trend prediction method using the crowdsourced wisdom of web search engines," *Data Technologies and Applications*, vol. 56, no. 5, pp. 741–761, 2022, doi: 10.1108/DTA-08-2021-0209.
- [22] T. Grief and E. Nikbakht, "Review of Blockchain and Emerging Applications," in *The Emerald Handbook of Blockchain for Business*, Emerald Publishing Limited, 2021, pp. 31–47.
- [23] S. A. Raza, L. Yarovaya, K. Guesmi, and N. Shah, "Google Trends and cryptocurrencies: a nonparametric causality-in-quantiles analysis," *International Journal of Emerging Markets*, 2022, doi: 10.1108/IJOEM-10-2021-1522.
- [24] S. Bag, M. S. Rahman, S. Gupta, and L. C. Wood, "Understanding and predicting the determinants of blockchain technology adoption and SMEs' performance," *International Journal of Logistics Management*, 2022, doi: 10.1108/IJLM-01-2022-0017.
- [25] A. Mohan, K. P. V. P. Sankar, M. Manohar K, and A. Peter, "Improving anti-money laundering in bitcoin using evolving graph convolutions and deep neural decision forest," *Data Technologies and Applications*, pp. 1–17, 2022, doi: 10.1108/DTA-06-2021-0167.

## BIOGRAPHIES OF AUTHORS



**Jae Won Choi**    is a undergraduate student researcher at Department of Computer Science within the Erik Jonsson School of Engineering and Computer Science at the University of Texas at Dallas in Texas, USA. His areas of research focus include data science, artificial intelligence, blockchain technology, gaming, and other related fields. He can be contacted at email: [jxc190057@utdallas.edu](mailto:jxc190057@utdallas.edu).



**Young Keun Choi**    is a professor at the Division of Business Administration at the School of Business and Economics, Sangmyung University in Seoul, The Republic of Korea. His research interests encompass diverse fields such as business analytics, data science, entrepreneurship, and technology management. He can be contacted at email: [penking1@smu.ac.kr](mailto:penking1@smu.ac.kr).