Disclosing the Relationship Between Nasdaq and Bitcoin via Artificial Intelligence Approach: Machine Learning and Deep Learning

Minjong Cheon, Hayoung Choi, Hanseon Joo, Ook Lee
Dept. of Information System, Hanyang University, Seoul, South Korea
Corresponding author: Ook Lee, Email: ooklee@hanyang.ac.kr

Cryptocurrency has grown in popularity recently, and people try to get revenue from investing in cryptocurrency because the fluctuation is much larger than the stock market. However, because of this characteristic, some people lose a huge amount of money all of a sudden, or some people are addicted to it. Some experts claim that Nasdaq and Bitcoin exhibit a similar trend, showing a positive relationship between the two. Therefore, our research tries to prove that hypothesis with an artificial intelligence approach. The close price of the Nasdaq was used as an input variable, while the close price from Bitcoin and Ethereum was set as the target. Our experiment involves two different steps, which are EDA and machine learning analysis. For the first experiment, correlation matrix and joint plots were plotted, and Nasdaq and Bitcoin showed high correlation. Furthermore, six different machine learning algorithms and two deep learning algorithms were utilized for the analysis, and their accuracy was assessed with RMSE and MAE. RMSE and MAE of two coins based on Nasdaq were 1837.09 and 1066.32 for Bitcoin and 127 and 96.8 for Ethereum price prediction. However, even though the GRU yielded higher RMSE and MAE compared to the machine learning algorithm, visualization indicated that GRU was more effective than the machine learning model. Even though our research reveals a lower RMSE and MAE score compared to similar existing research, our finding is outstanding in that we proved that there exists a positive relationship between Nasdaq and Bitcoin.

Keywords: cryptocurrency, Nasdaq, bitcoin, Ethereum, machine learning, deep learning, LGBM, LinearRegressor

2023. In Saroj Hiranwal & Garima Mathur (eds.), *Artificial Intelligence and Communication Technologies*, 1053–1062. Computing & Intelligent Systems, SCRS, India. https://doi.org/10.52458/978-81-955020-5-9-100

1. Introduction

A. Background

Cryptocurrency has become one of the most trending topics nowadays[1]. It is a peer-to-peer-based online transaction system that basically does not rely on bank-based transactions[2]. Its name originated from encryption technology which could authenticate every transaction[https://www.investopedia.com/terms/c/cryptocurrency.asp]. Even though this technology has not been widely applied in reality until recently[3], people are always paying attention to it for investment[4]. As an alternative investment, many investors around the world are interested in cryptocurrency[5], and it's an efficient approach to increasing assets[6]. However, as the fluctuation of cryptocurrencies is far larger than the stock market[7], many investors lose a considerable amount of cash in a moment[8], and some experts argue that investing in cryptocurrencies is similar to gambling[9][10]. While the stock market has been studied for a long time, some experts found out that political instability, interest rates, current events, currency volatility, and natural disasters could affect the price of stocks, making it much easier for investors to predict the price [11]. However, as mentioned above, cryptocurrency's fluctuation is much larger, and even a single word from a celebrity could yield a tremendous impact on prices. For instance, tweets from Elon Musk and Mark Cuban raised the price of Dogecoin[12]. Therefore, many researchers have utilized machine learning or deep learning algorithms to predict the price accurately[13][14][15], and the figure below reveals an increasing Bitcoin prediction research from 2015 to 2021[16].

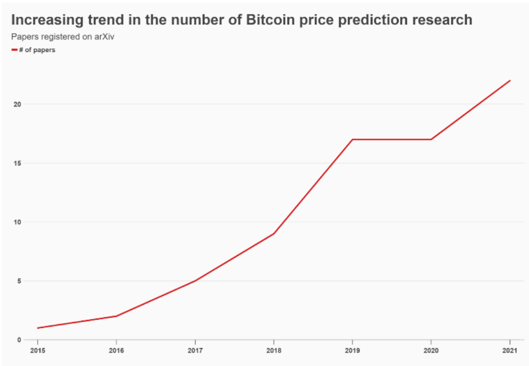

Fig. 1 Increasing trend in the number of Bitcoin Price Prediction Researches

B. Objective

However, some experts claim that, unlike before, Bitcoin is shifting concurrently with U.S stocks[17]. In other words, they insist that there is a positive correlation between the two. Therefore, through this research, we aim to prove the theorem with artificial intelligence. We utilized diverse machine learning and deep learning algorithms to predict the price of Bitcoin. The price of Nasdaq is used as an input variable and the price of Bitcoin as a target. Furthermore, this approach will also be applied to the other more fluctuating cryptocurrencies, which could help scrutinize the impact of the Nasdaq on various cryptocurrencies. Our experiment consists of two different stages: EDA and applying machine learning models to prove the hypothesis of the experts.

2. Related Works

Velankar et al. focused on Bitcoin price predicting via various parameters. They used a time-series dataset containing daily Bitcoin prices, acquired from Quandl and CoinmarketCap. Log transformation, z-score normalization, and box cox normalization are used to normalize the data, and features such as block size, total bitcoins, day high and day low, number of transactions, and trade volume are selected to be fed to the predictive network. Velankar et al. conducted two analyses, Bayesian Regression and GLM/Random Forest. In the first analysis, they divided the data into three parts and applied k-means clustering to the first third of the data, Bayesian Regression to the second, and evaluated the algorithm with the third. On the second analysis, they constructed three-time series data sets for 30, 60, and 120 minutes and ran GLM/Random Forest on each of the two time-series data sets separately. The main contribution of the paper is that they established the learning framework and completed the normalization, proposing two methods to predict Bitcoin prices [18].

As cryptocurrency has fluctuated due to various uncertainties, the need for an automation tool that predicts the market has increased. Ferdiansyah et al. propose LSTM, another type of module provided for RNN, in predicting Bitcoin price. The database consists of time-series data of Bitcoin prices for five years and is collected from the yahoo finance stock market (based on the USD exchange rate) and CCC. RMSE was the lowest, 288.59866; when the researchers used 500 epochs, model dropout was set to 0. The model provided the prediction result, but the RMSE score showed that the result was not good enough. Thus, Ferdiansyah et al. found that LSTM is not good enough to make the decision to invest in bitcoin, concluding with the importance of uncertain factors such as political issues and economic issues on Bitcoin prices [19].

Phaladisailoed and Numnonda used the Kaggle website to acquire data on 1-minute interval trading exchange rates in USD from January 1, 2012, to January 8, 2018. To anticipate the goal, four features (latest trade, opening trade, highest trade during day, lowest trade throughout the day) were used (weighted price). GRU, a less complicated model of LSTM, projected the lowest MSE of 0.00002. GRU's reset gate determines how much prior state data may be utilized with current input data, whereas an update gate determines how much past state data to acquire. Although changing the hyperparameter can have an impact on GRU's performance, GRU had the highest MSE score. Furthermore, four characteristics were insufficient to forecast bitcoin prices because many other factors influence its price of it[20].

McNally et al. utilized a dataset of Bitcoin's USD closing price, collected from the Coindesk Bitcoin Price Index. ARIMA, Bayesian optimized recurrent neural network (RNN), and a Long Short Term Memory (LSTM) network were utilized to predict the price. The Bitcoin dataset from the 19th of August 2013 until the 19th of July 2016 was used for training their models. Their research yielded that the performance of the ARIMA model was the lowest, and the LSTM showed the best one, achieving an accuracy of 52% and an RMSE of 8%. Furthermore, they also compared the CPU to GPU during their training, and they concluded that using GPU surpassed the CPU [21].

Wang H. et al. examined asymmetric contagion effects between stock and cryptocurrency markets through GARCH models. GARCH models describe financial markets in which volatility can change, becoming more volatile during times of financial crises or world events and less volatile during times of relative calm and steady economic growth. This research found dynamic correlations between these two types of financial markets using the GARCH model [22].

3. Materials and Methods

A. Data Description

The dataset provides the Nasdaq Composite Index, Ethereum, and Bitcoin prices from January 2, 2018, to March 25, 2022. The data is provided from [23] for the Nasdaq Composite Index, [24] for Bitcoin, and [25] for Ethereum. It consists of data and the closing price of the Nasdaq Composite Index, Ethereum, and Bitcoin, and those variables are visualized in the figure below, figure 2.

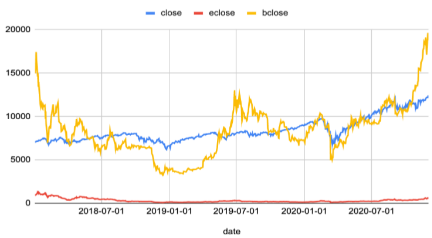

Fig. 2 Visualization of the given dataset: close price from Nasdaq, Bitcoin, and Ethereum

B. Experiment Pipeline

Our experiment includes several steps. First, exploratory data analysis was performed to prove the hypothesis. Second, the dataset was split into the train and test datasets, and various machine learning models yielded RMSE, MAE, and R2 scores. Those procedures are visualized in the figure 3.

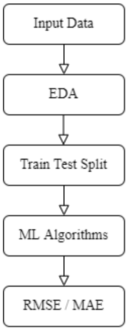

Fig 3 Visualization of the Experimental Pipeline in the Research

C. EDA

Exploratory Data Analysis(EDA) was conducted to explain the characteristics of the given dataset. To better understand data, exploratory data analysis (EDA) uses descriptive statistics and graphical tools[26]. The 'Close' column denotes the close price of Nasdaq, while the 'eclose' and the 'bclose' column denotes the close price of Bitcoin and Ethereum, respectively. First of all, the correlation between each variable was analyzed, and it showed that the correlation between Nasdaq and Bitcoin was higher than that of Nasdaq and Etherium, which showed 0.64 and -0.03, respectively. Furthermore, joint plot functions were applied to the dataset to discover the relationship between two variables[27], and those joint plot graphs showed the same result as the correlation matrix, which is shown in figure 4.

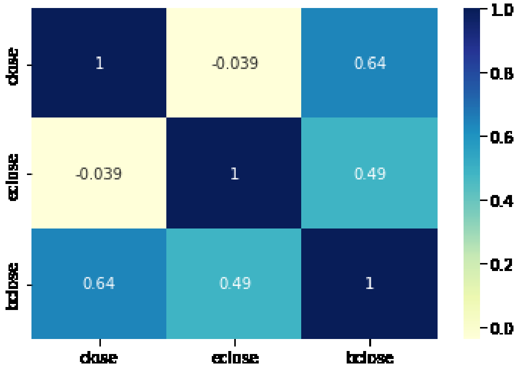

Fig 4. Visualization of Correlation Matrix Between Variable Through Heat Map

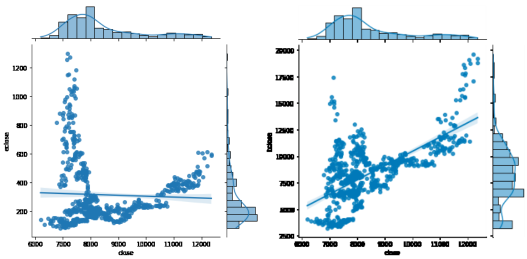

Fig 5 Visualization of Joint Plots from the Input Variables

D. GRU

Gated recurrent unit (GRU) belongs to the deep learning algorithms. While the deep neural network (DNN) is a basic form of deep learning consisting of multiple layers such as input, hidden, and output, the architecture of the GRU has differences. GRU is similar to the long short term memory (LSTM)[28] and recurrent neural network (RNN)[29]. Those algorithms overcome the vanishing gradients problem of the RNN, and therefore they are specialized in dealing with time-series data [30]. GRU primarily consists of two gates: a reset gate and an update gate [31]. The reset gate's aim is to reset the past data from prior concealed levels. The update gate determines a proportion of both current and historical information, and the update gate's output manages the quantity of information available at any particular time [32]. The overall architecture of the model is described in the following figure: figure 5.

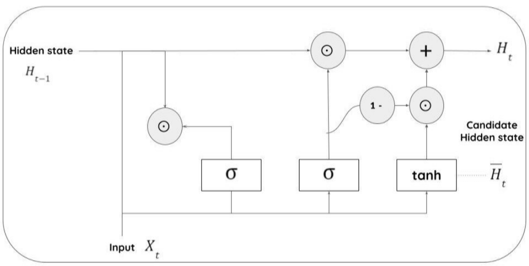

Fig 6. The Architecture of the Gated Recurrent Unit (GRU)

E. LGBM

The light gradient boosting machine(LGBM) is now widely used in various studies, as the performance of the model is outstanding. This model belongs to supervised learning and a developed version of the boosting algorithms. As the previous boosting models consisted of downsides in dealing with large memory, the LGBM overcame that with novel approaches: gradient based one side sampling(GOSS), and exclusive feature bundling (EFB) [33].

4 Result

To predict the bitcoin price, various machine learning models were utilized, including decision tree, linear regression, extreme gradient boosting(XGB), gradient boosting, random forest, and light gradient boosting machine. Root mean squared error(RMSE) and mean absolute error (MAE) were analyzed to evaluate those models. In addition, prediction and real price were plotted for better understanding, which could be found in the figures below. The lowest RMSE and MAE when predicting the Bitcoin price from the Nasdaq price were 1837.09 and 1066.32, while 197.12 and 157.09 for predicting the Ethereum price, and those values are described in figures 6 and 7. Figure 8 and figure 9 show the comparison of predicted value and real value.

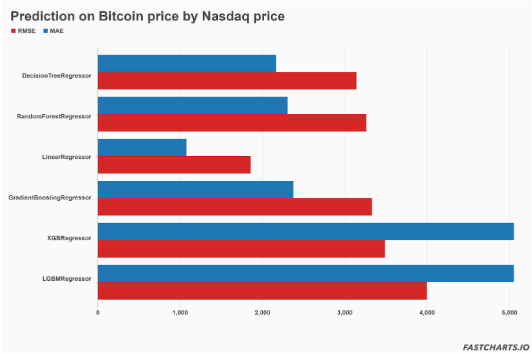

Fig 7. Visualization of the Results from Predicting Bitcoin Price by Nasdaq Price

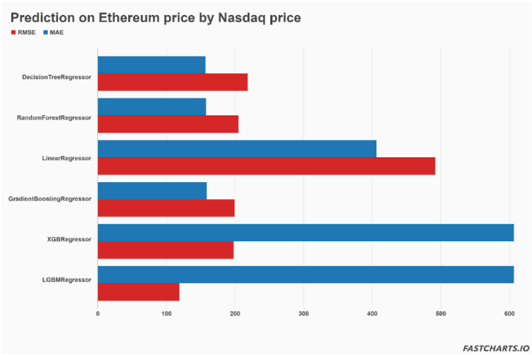

Fig 8. Visualization of the Results from Predicting Ethereum Price by Nasdaq Price

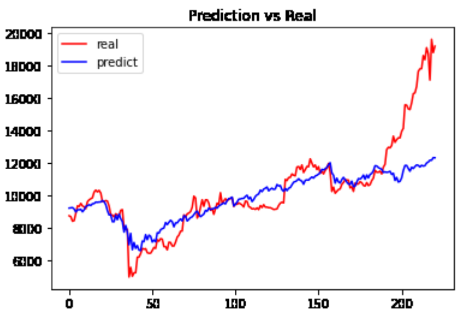

Fig 9 Plotting Results from Pedicting Bitcoin Price by Nasdaq Price

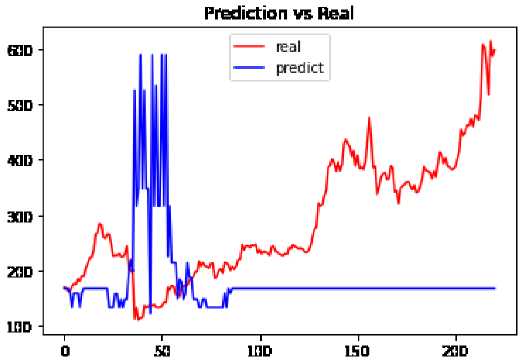

Fig 10 Plotting Results from Pedicting Ethereum Price by Nasdaq Price

Figure 10 illustrated deep learning algorithms such as LSTM and GRU were also utilized for the prediction of the Bitcoin price. As the graphs below indicate, GRU achieved a more accurate prediction compared to the LSTM. GRU achieved 2336.2 and 1351 for RMSE and MAE, respectively, while the LSTM yielded 2633.3 and 1675.

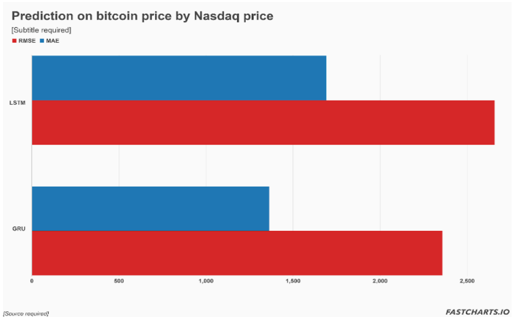

Fig 11. Visualization of the Results from Predicting Bitcoin Price by Nasdaq Price(Deep Learning)

Figure 11 showed deep learning algorithms such as LSTM and GRU were also utilized for the prediction of the Bitcoin price. As the graphs below indicate, GRU achieved a more accurate prediction compared to the LSTM. GRU achieved 2336.2 and 1351 for RMSE and MAE, respectively, while the LSTM yielded 2633.3 and 1675.

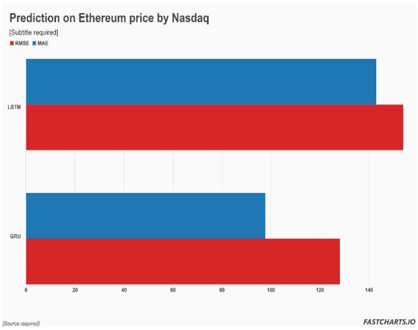

Fig 12. Visualization of the Results from Predicting Ethereum Price by Nasdaq Price(GRU)

Figure 12 and figure 13 exhibited plotting results by Bitcoin and Ethereum price, respectively, and it could be concluded that predicting the Bitcoin is more accurate than the Ethereum.

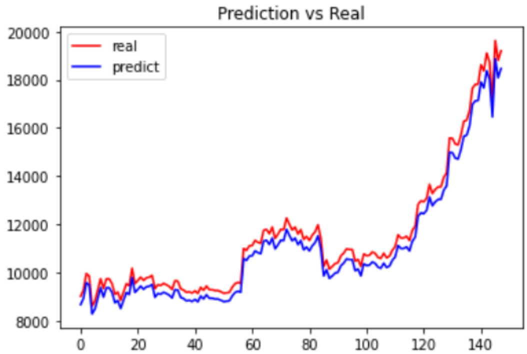

Fig 13. Plotting Results from Predicting Bitcoin Price by Nasdaq Price(GRU)

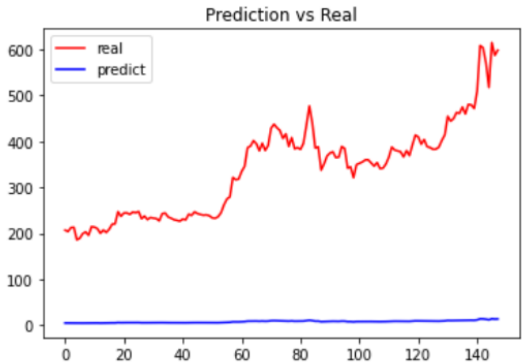

Fig 14. Plotting Results from Predicting Ethereum Price by Nasdaq Price(GRU)

5 Discussion

The principal finding of this research is that we figured out the relationship between Nasdaq and Bitcoin prices, especially compared with Ethereum. Through the EDA, both correlation matrix and joint plots indicated that Nasdaq has a higher correlation with Bitcoin than Ethereum. Furthermore, machine learning and deep learning algorithms showed that predicting the Bitcoin price with the Nasdaq price is more accurate than predicting the Ethereum price with the Nasdaq price. However, there also exists a limitation that the RMSE and MAE values from the algorithms were not that low compared with other previous research[34][35]. With the limitation, we conclude that other economical, social, or political features should be considered to precisely predict the Bitcoin price, which is distinguishable from other research.

6. Conclusion

As some experts have claimed that Nasdaq and Bitcoin have a positive relationship, our team conducted research on proving that claim by comparing the effect of Nasdaq on Bitcoin and Ethereum via a machine learning-based approach. The dataset for Nasdaq and each cryptocurrency was collected from different sources from 2018 to 2020. Through the EDA process, plotting joint plots, and correlation matrix, high correlations between Nasdaq and Bitcoin were confirmed. Furthermore, six different machine learning models and two deep learning models displayed more precision in predicting Bitcoin than Ethereum with Nasdaq. The two analyses conclude that there exists a positive correlation between Nasdaq and Bitcoin. Though the RMSE and MAE score is higher than those of similar research, unveiling the relationship between the Nasdaq and Bitcoin makes our research remarkable.

References

[1] Wang, X., Chen, X., & Zhao, P. (2020). The relationship between Bitcoin and stock market. International Journal of Operations Research and Information Systems, 11(2), 22–35. https://doi.org/10.4018/ijoris.2020040102

[2] Ad Hegadekatti, K., & S G, Y. (2017). The programmable economy: Envisaging an entire planned economic system as a single computer through Blockchain Networks. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2943227

[3] Chuen, D. L. E. E. K., Guo, L., & Wang, Y. (2017, December 31). Cryptocurrency: A new investment opportunity?The Journal of Alternative Investments. Retrieved May 24, 2022, from https://doi.org/10.3905/jai.2018.20.3.016

[4] Árnason, S. L. (1970, January 1). [PDF] cryptocurrency and Bitcoin. A possible foundation of future currency: Why it has value, what is its history and its future outlook: Semantic scholar. undefined. Retrieved May 24, 2022, from https://www.semanticscholar.org/paper/Cryptocurrency-and-Bitcoin.-A-possible-foundation-%C3%81rnason/62f60f6f2805c340a0694629aa66b54726fb6b8a

[5] M., P., Sharma, A., V., V., Bhardwaj, V., Sharma, A. P., Iqbal, R., & Kumar, R. (2020). Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. Computers & Electrical Engineering, 81, 106527. https://doi.org/10.1016/j.compeleceng.2019.106527

[6] Platanakis, E., & Urquhart, A. (2020). Should investors include Bitcoin in their portfolios? A portfolio theory approach. The British Accounting Review, 52(4), 100837. https://doi.org/10.1016/j.bar.2019.100837

[7] Ben, S., & Xiaoqiong, W. (2019, August 1). Are cryptocurrencies good investments?Studies in Business and Economics. Retrieved May 24, 2022, from https://sciendo.com/article/10.2478/sbe-2019-0033

[8] Scott A. Wolla, "Bitcoin: Money or Financial Investment?,"Page One Economics®, March 2018

[9] Addiction experts warn of cryptocurrency 'gambling.' (n.d.). The TImes. Retrieved April 6, 2022, from https://www.google.com/search?q=bitcoin+addicted&rlz=1C5CHFA_enKR961KR961&source=lnms&tbm=nws&sa=X&ved=2ahUKEwimuPS8uP32AhULQd4KHbIlAngQ_AU0AX0ECAEQAw&biw=1440&bih=678&dpr=2

[10] O'Donoghue, P. (2022, April 3). Addiction experts warn of cryptocurrency 'gambling.' Ireland | The Sunday Times. Retrieved April 25, 2022, from https://www.thetimes.co.uk/article/addiction-experts-warn-of-cryptocurrency-gambling-sf625f2ng

[11] Why users are pushing back against the world's largest crypto exchange. (2022, April 1). The Washington Post. Retrieved April 6, 2022, from https://www.washingtonpost.com/outlook/2022/04/01/binance-may-19-lawsuit-cryptocurrency/

[12] C. (2022, February 15). Factors Affecting Stock Market. ABC of Money. Retrieved April 6, 2022, from https://www.adityabirlacapital.com/abc-of-money/factors-affecting-stock-market#:%7E:text=The%20stock%20market%20is%20affected,to%20buy%20or%20sell%20stocks.

[13] [13] Browne, R. (2021, April 28). Dogecoin price surges after tweets from Elon Musk and Mark Cuban. CNBC. Retrieved April 6, 2022, from https://www.cnbc.com/2021/04/28/dogecoin-price-surges-after-tweets-from-elon-musk-and-mark-cuban.html

[14] Akyildirim, E., Goncu, A., & Sensoy, A. (2020). Prediction of cryptocurrency returns using machine learning. Annals of Operations Research, 297(1-2), 3–36. https://doi.org/10.1007/s10479-020-03575-y

[15] Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. Journal of Information Security and Applications, 55, 102583. https://doi.org/10.1016/j.jisa.2020.102583

[16] Alessandretti, L., ElBahrawy, A., Aiello, L. M., & Baronchelli, A. (2018). Anticipating cryptocurrency prices using machine learning. Complexity, 2018, 1–16. https://doi.org/10.1155/2018/8983590

[17] Search | arXiv e-print repository. (n.d.). Arxiv. Retrieved April 6, 2022, from https://arxiv.org/search/?query=bitcoin&searchtype=all&source=header

[18] Jagtiani, S. (2022, January 25). Bitcoin Is Moving in Tandem With Stocks Like Never Before. Bloomberg. Retrieved April 6, 2022, from https://www.bloomberg.com/tosv2.html?vid=&uuid=90b065c4-b509-11ec-b0be-

6755456c6e47&url=L25ld3MvYXJ0aWNsZXMvMjAyMi0wMS0yNS9iaXRjb2luLWlzLW1vdmluZy1pbi10YW5kZW0td2l0aC1zdG9ja3MtbGlrZS1uZXZlci1iZWZvcmUtY2hhcnQ=

[19] Velankar, S., Valecha, S., & Maji, S. (2018). Bitcoin price prediction using machine learning. 2018 20th International Conference on Advanced Communication Technology (ICACT) https://doi.org/10.23919/icact.2018.8323676

[20] Ferdiansyah, F., Othman, S. H., Zahilah Raja Md Radzi, R., Stiawan, D., Sazaki, Y., & Ependi, U. (2019). A LSTM-Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market. 2019 International Conference on Electrical Engineering and Computer Science (ICECOS). https://doi.org/10.1109/icecos47637.2019.8984499

[21] Phaladisailoed, T., & Numnonda, T. (2018). Machine Learning Models Comparison for Bitcoin Price Prediction. 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE). https://doi.org/10.1109/iciteed.2018.8534911

[22] McNally, S., Roche, J., & Caton, S. (2018). Predicting the Price of Bitcoin Using Machine Learning. 2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP). https://doi.org/10.1109/pdp2018.2018.00060

[23] Wang, H., Wang, X., Yin, S., & Ji, H. (2022). The asymmetric contagion effect between stock market and cryptocurrency market. Finance Research Letters, 46, 102345. https://doi.org/10.1016/j.frl.2021.102345

[24] NASDAQ Composite 과거 금리 - Investing.com. (n.d.). Investing.com. Retrieved April 6, 2022, from https://kr.investing.com/indices/nasdaq-composite-historical-data

[25] Bitcoin Data. (2022, March 25). Kaggle. Retrieved April 6, 2022, from https://www.kaggle.com/datasets/varpit94/bitcoin-data-updated-till-26jun2021 etherium. (2019, November 7). Kaggle. Retrieved April 6, 2022, from https://www.kaggle.com/datasets/hamdinizar/etherium

[26] Camizuli, E., & Carranza, E. J. (2018). Exploratory Data Analysis (EDA). The Encyclopedia of Archaeological Sciences, 1–7. https://doi.org/10.1002/9781119188230.saseas0271

[27][27] Seaborn.jointplot¶. seaborn.jointplot - seaborn 0.11.2 documentation. (n.d.). Retrieved May 24, 2022, from https://seaborn.pydata.org/generated/seaborn.jointplot.html

[28] Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014).Empirical evaluation of gated recurrent neural networks on sequence modeling. InNIPS 2014 Workshop on Deep Learning, December 2014 https://doi.org/10.48550/arXiv.1412.3555

[29] ArunKumar, K. E., Kalaga, D. V., Mohan Sai Kumar, C., Kawaji, M., & Brenza, T. M. (2022). Comparative analysis of gated recurrent units (GRU), long short-term memory (LSTM) cells, autoregressive integrated moving average (ARIMA), Seasonal Autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends. Alexandria Engineering Journal, 61(10), 7585–7603. https://doi.org/10.1016/j.aej.2022.01.011

[30] Hochreiter, S. (1998). The vanishing gradient problem during learning recurrent neural nets and problem solutions. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 6(02), 107-116.

[31] Joo, H., Choi, H., Yun, C., & Cheon, M. (2022b). Efficient Network Traffic Classification and Visualizing Abnormal Part Via Hybrid Deep Learning Approach : Xception + Bidirectional GRU. Global Journal of Computer Science and Technology, 1–10. https://doi.org/10.34257/gjcsthvol21is3pg1

[32] Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.

[33] Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., ... & Liu, T. Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. Advances in neural information processing systems, 30.

[34] Phaladisailoed, T., & Numnonda, T. (2018). Machine learning models comparison for bitcoin price prediction. 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE). https://doi.org/10.1109/iciteed.2018.8534911

[35] Aggarwal, A., Gupta, I., Garg, N., & Goel, A. (2019). Deep Learning Approach to determine the impact of socio economic factors on Bitcoin Price prediction. 2019 Twelfth International Conference on Contemporary Computing (IC3). https://doi.org/10.1109/ic3.2019.8844928