Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 3, No. 2, June, 2022

Social Network Analysis of Cryptocurrency using Business Intelligence Dashboard

Jonathan C. Setyono [1*], William S. Suryawidjaja [1], Abba S. Girsang [2]

[1] *Computer Science Department, School of Computer Science, Bina Nusantara University, Jakarta, 11480, Indonesia.*

[2] *Computer Science Department, BINUS Graduate Program-Master of Computer Science Bina Nusantara University, Jakarta 11480, Indonesia.*

Received 04 February 2022; Revised 22 April 2022; Accepted 11 May 2022; Published 01 June 2022

Abstract

There are currently more than 10.000 cryptocurrencies available to buy from the online market, with a vast range of prices for each coin it sells. The fluctuation of each coin is affected by any social events or by several important companies or people behind it. The aim of this research is to compare three cryptocurrencies, which are Bitcoin, Ethereum, and Binance Coin, using Social Network Analysis (SNA) by visualizing them using Business Intelligence (BI Dashboard). This study uses the SNA parameters of *degree*, *diameter*, *modularity*, *centrality*, and *path length* for each network and its actors and their actual market price by *crawling* (data collecting process) from Twitter as one of the social media platforms. From the research conducted, the popularity of cryptocurrencies is affected by their market price and the activeness of their actors on social media. These results are important because they could help in the decision-making to buy cryptocurrencies with high popularity on social media because they tend to retain their value over time and could benefit from price spikes from influential people.

Keywords: Business Intelligence; Cryptocurrency; Social Network Analysis; Social Media.

---

1. Introduction

In this era, social media has become something that cannot be separated from our lives. It gives us the ability to share our thoughts with the whole world [1]. According to Perrin (2015) [2], nearly two-thirds of adults in the United States (65%) use social networking sites, with the most likely users of social media being young adults (ages 18 to 29). Hence, every trending topic such as cryptocurrency will surely be discussed on social media. Cryptocurrency itself is a form of digital currency that has been rapidly growing over a short time [3] since the introduction of Bitcoin in 2008 [4]. The reason behind this phenomenon is that cryptocurrency allows us to do public transactions without centralized authority's approval over the Internet, even though there are still trust issues regarding the cryptocurrency ecosystem, such as price manipulation, questionable privacy and security, lack of regulation from the government, and insiders' trading [5].

According to the coinmarketcap.com website, there are currently 17.024 cryptocurrencies on sale with a wide range of prices per coin from under one United States Dollar (USD) to an astounding price of above 100.000 USD and 149 categories such as stablecoin, energy, and event cryptocurrencies. Worldwide events could also affect cryptocurrencies' prospects e.g. [6] where Dogecoin – one of the cryptocurrency tokens – was having a significant price effect just by the tweet on Twitter by influential individual like Elon Musk. Thus, selecting cryptocurrencies that are worth buying has become quite a formidable challenge.

---

* Corresponding author: jonathan.setyono@binus.ac.id

http://dx.doi.org/10.28991/HIJ-2022-03-02-09

Previous studies have been done for searching worth-to-buy cryptocurrencies by using social network analysis. A network analysis of 69 cryptocurrencies during COVID-19 has been done by using descriptive statistics and social network analysis [7]. Vidal-Tomás (2021) [7] used *degree centrality*, *betweenness centrality*, *average degree centrality*, and *average betweenness centrality* to inspect cryptocurrencies' social network analysis. Another research utilized webometrics analysis and social network analysis with the indicators of *degree*, *eigenvector*, *closeness*, and *betweenness centralities* to examine 53 cryptocurrencies' performance [8]. Meanwhile, Alqassem et al. (2020) [9] applied social network analysis' *diameter* parameter to capture the event of shrinking diameter on their study. Other studies that were conducted by Javarone & Wright (2018) [10] implemented *degree* to see Bitcoin's network *degree distribution*, *clustering coefficient*, and *path length* from social network analysis as well as [11] utilized *average degree* and *clustering* social network analysis to compare Bitcoin and Ethereum as cryptocurrency tokens.

On the other hand, some research does not use social network analysis when analyzing cryptocurrencies. A study conducted by Pilar et al. (2018) [12] used a hierarchical method which is *a minimum spanning tree* to explain the correlation between 16 cryptocurrencies. Meanwhile, Sohaib et al. (2020) [13] utilized Partial Least Squares – Structural Equation Modeling (PLS-SEM) to analyze cryptocurrencies. Another research by Biryukov & Tikhomirov (2019) [14] used the clustering method as well as Lin et al. (2020) [15] proposed an embedding model to inspect cryptocurrencies' transactions. Also, Ji et al. (2019) [16] did a study to analyze network correlation between cryptocurrencies.

From the observed literatures, most research has been focusing on comparing cryptocurrencies using network analysis from social media and other parameters for each cryptocurrency overview but without utilizing data visualization techniques. Our proposed approach for analysing cryptocurrencies is to implement Business Intelligence (BI) Dashboard to present the social network analysis. Social network analysis is used to examine cryptocurrencies' network overview and their actors or people that posted and interacted with others regarding the related cryptocurrency in social media. A BI Dashboard can process, store, report, and examine data to display the fact that could be used to make decisions [17]. BI will be helpful to compare multiple cryptocurrencies using social network parameters by displaying the analyzed parameters with data visualization and other features that are provided by the BI Dashboard platform such as embedding a website content to show the real-time price of cryptocurrencies as well as the easiness of creating and sharing a BI Dashboard to other parties.

2. Materials and Methods

2.1. Social Network Analysis

This research uses Social Media Network Analysis (SMNA) methodology as the implementation of Social Network Analysis (SNA). According to Camacho et al. (2021) [18], the difference between SMNA and SNA is in the data collecting process. On SMNA, the data that is used in the research already existed in the form of a digital footprint from social media. Meanwhile, research design and method of collecting data such as interview or observation are needed on SNA methodology as presented in Figure 1.

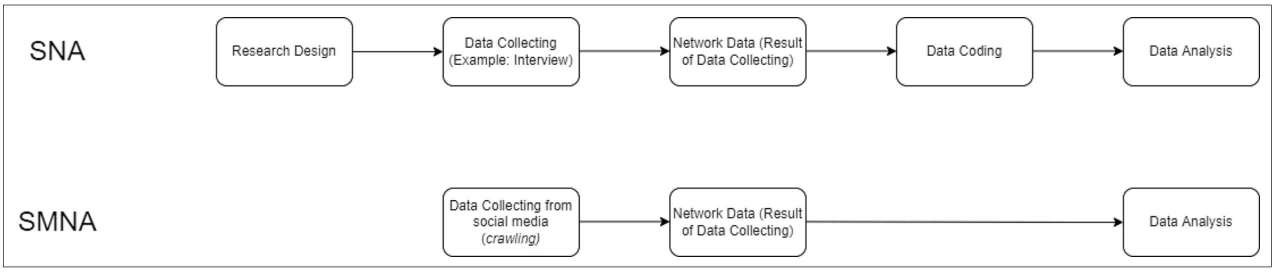

Figure 1. Differences between SNA and SMNA methodology

Data collecting process which can be called *crawling* utilized the open-source website application Netlytic. This research chose three cryptocurrencies to be compared which are Bitcoin, Ethereum, and Binance Coin. Then, *crawling* technique is used for those cryptocurrencies from Twitter using our defined query. Our query searched for tweets (post on Twitter) that includes keywords of BTC or Bitcoin for Bitcoin, ETH or Ethereum for Ethereum, and BNB or Binance for Binance Coin with the posts' language of English and retweet as shown in Figure 2(a), 2(b), 2(c).

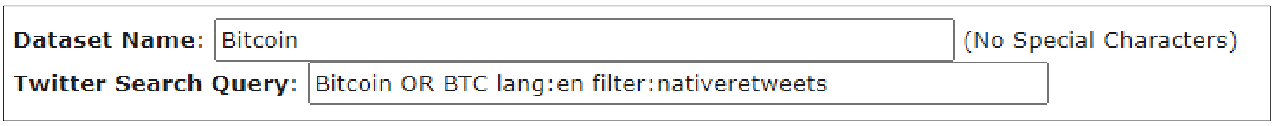

Figure 2(a). Twitter search query for Bitcoin in Netlytic

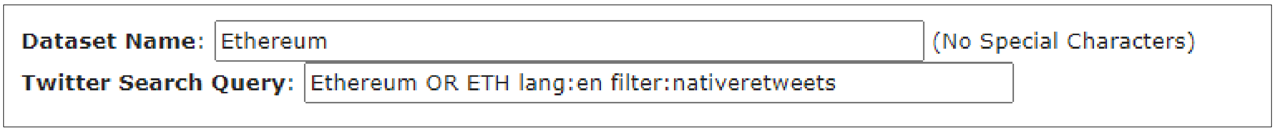

Figure 2(b). Twitter search query for Ethereum in Netlytic

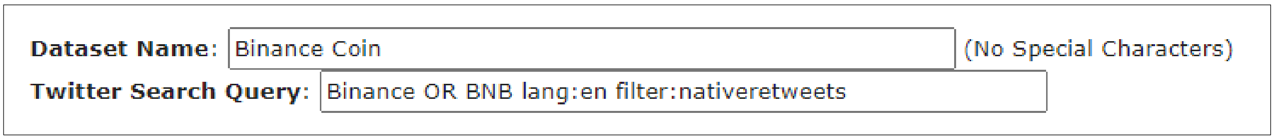

Figure 2(c). Twitter search query for Binance Coin in Netlytic

2500 rows of records were taken from Netlytic for each of the cryptocurrencies to be processed for Social Network Analysis. Our next procedure is visualizing the cryptocurrencies' network overview user graph and exporting each of the cryptocurrencies into the Gephi file (.gexf) because Gephi has a more comprehensive social network analysis tools than Netlytic but is not able to do data *crawling* on the free version. The social network analysis step is done through Gephi where they were processed from the exported files and changed to an undirected graph and examined the *degree*, *diameter*, *modularity*, *centrality*, and *path length*. Instead of only using the network properties overview as in [7-11], our study used each actor's social network properties for example each actor degree value. After the process is completed, the analyzed cryptocurrencies then are exported into a .csv file to be processed on the next process which is Data Warehouse.

2.2. Social Network Analysis Parameters Social Network Analysis

Degree: Degree or degree centrality is the number of relations (link) that an actor (a node) has between the actor and other actors on the network [19].

***Diameter*:** Diameter is the value of proximity regarding two pairs of actors or nodes in a network to give information about how far they both are [20].

***Modularity*:** Modularity is a measure of a network's modularity by describing structures that detect community or group in a network [21]. According to Aditama & SN (2020) [21], a group in modularity means that the actors inside have more intense connection than to actors outside the group.

***Centrality*:** Centrality score refers to the most important actor(s) in the network [22]. A network with a high centrality value (centralized network) means that there are dominant actors where a lot of nodes are connected to them.

***Path Length*:** Path Length is the score given to indicate how far two actors are separated by calculating how many actors or nodes are between them. A social network with a shorter path length score makes transmitting information between two actors more efficient [23].

***Path Length*:** Path Length is the score given to indicate how far two actors are separated by calculating how many actors or nodes are between them. A social network with a shorter path length score makes transmitting information between two actors more efficient [23].

2.3. Data Warehouse

From the .csv files that contain social network analysis of each cryptocurrency, Pentaho is used as software to do the Extract-Transform-Load (ETL) process. The ETL procedures for every cryptocurrency are: i) Extracting data from .csv files. ii) Transform the extracted data to match the database design as in Figure 4. iii) Load or insert the data into the database that has been designed as in Figure 3. SQL Server Management Studio (SSMS) is used as our SQL database infrastructure to keep the cryptocurrencies' social network analysis records.

Star Schema concept is an Online Analytical Processing (OLAP) schema that puts a fact table on the center of the database design and the dimension tables around it [24]. Our database design consists of SocialNetworkFact that records other table primary keys as foreign keys and every actor's social network analysis parameter, UserDim that records actors' information from Twitter, TimeDim that records the time of social network analysis process, and NetworkOverviewDim that records each of the cryptocurrencies' social network parameter.

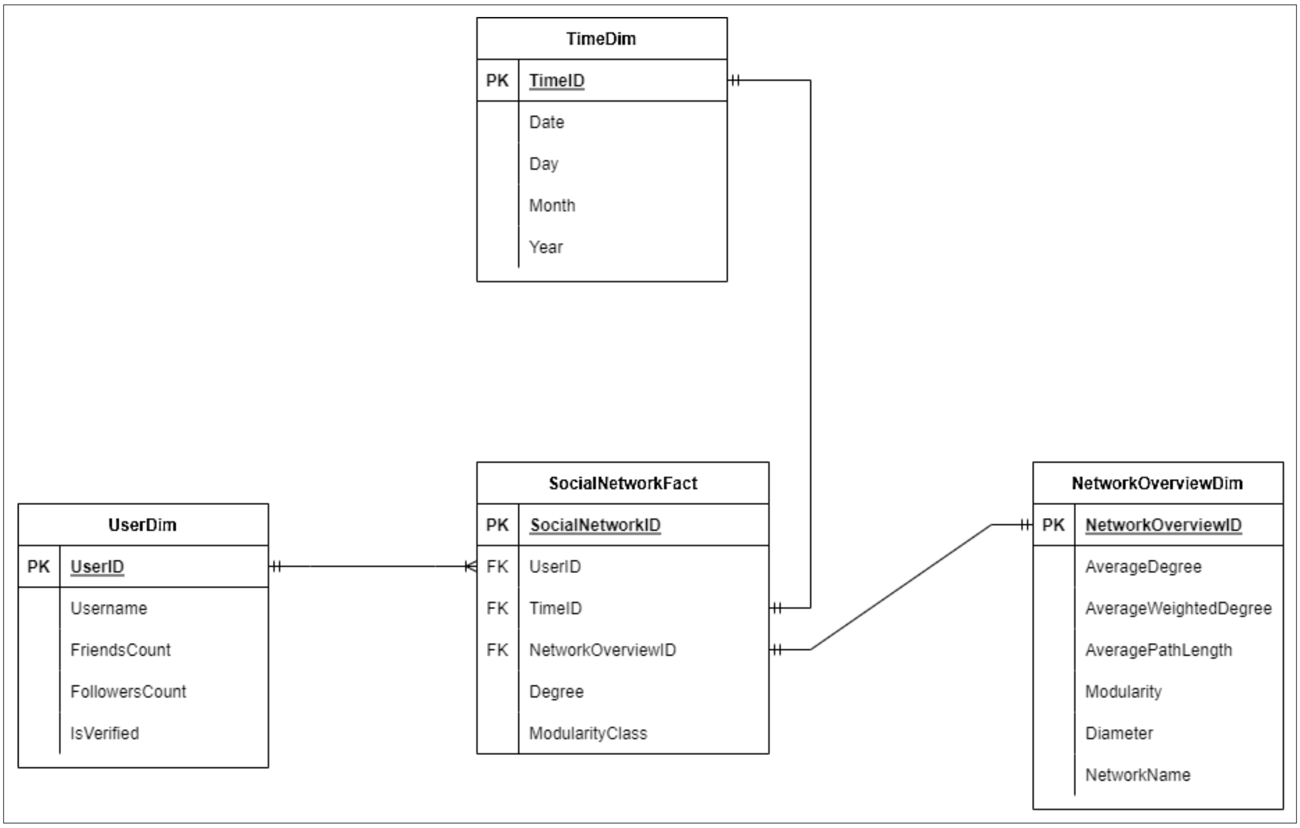

Figure 3. Database design for Data Warehouse using Star Schema concept

2.4. Business Intelligence (BI) Dashboard

Business Intelligence (BI) is a technique to blend data gathering, storage, and knowledge management to provide data-driven analytics that helps the decision-making process [25]. There are many BI platforms that could create BI Dashboards such as Tableau and Qlik Sense, but PowerBI is chosen to be used as this research BI Dashboard because the provided features fit perfectly with the features that were needed. There are two separate programs that are used for creating the BI Dashboard which is PowerBI Desktop and PowerBI website at powerbi.microsoft.com. PowerBI Desktop is utilized to connect data sources which are SQL Server in our case and to publish them into the PowerBI website. PowerBI website then allows us to create reports and a cryptocurrencies' comparison SNA dashboard. A report in PowerBI is a single page that contains visualization elements such as graphs and cards to display data that are going to be analyzed from the dataset [26]. Meanwhile, according to Sun et al. (2016) [26], a dashboard is a feature that contains multiple published reports whether the whole or only selected reports.

3. Results and Discussion

To gather all the beneficial information for Social Network Analysis, this study proposed the design of our BI Dashboard be divided into three parts which are the cryptocurrencies' network overview, social network analysis, and the actors of each cryptocurrency's social network analysis. It is useful to display specific information regarding the different classes of specific data.

3.1. Cryptocurrencies Network Overview

The design of network overview for each cryptocurrency consists of the SNA parameters value, SNA user graph, and the market price as shown in Figure 4(a), 4(b), 4(c). The coinlib.io website is utilized to use web content input in PowerBI for presenting the market price of the cryptocurrencies. The SNA user graph is displayed using pictures that are exported from Netlytic and the SNA parameters value of average *path length*, average *degree*, *diameter*, and *modularity* is presented. Based on the results below in Figure 5(a), 5(b), 5(c), Binance's social network has the best SNA indicators because of the smaller nature of network scale in Twitter or least popular cryptocurrency token in Twitter.

Binance has the easiest network for the actors to reach each other (smallest average *path length* and *diameter* value) and the highest relation of *degree* value on each actor or node. Meanwhile, Bitcoin's social network excelled in *modularity* which means that the groups in Bitcoin's network have the highest average interaction. On the other hand, Ethereum's social network is the most difficult for the actors to reach each other because of the biggest average *path length* and *diameter* value.

The market price of cryptocurrencies also has a correlation with the SNA. Because of higher market value e.g., Bitcoin has the most expensive cryptocurrency token price, the social network is bigger than the other because it is more popular on Twitter than the likes of Binance Coin which has the least token price. Therefore, it is easier for Binance Coin to have a better connection with each actor on the network.

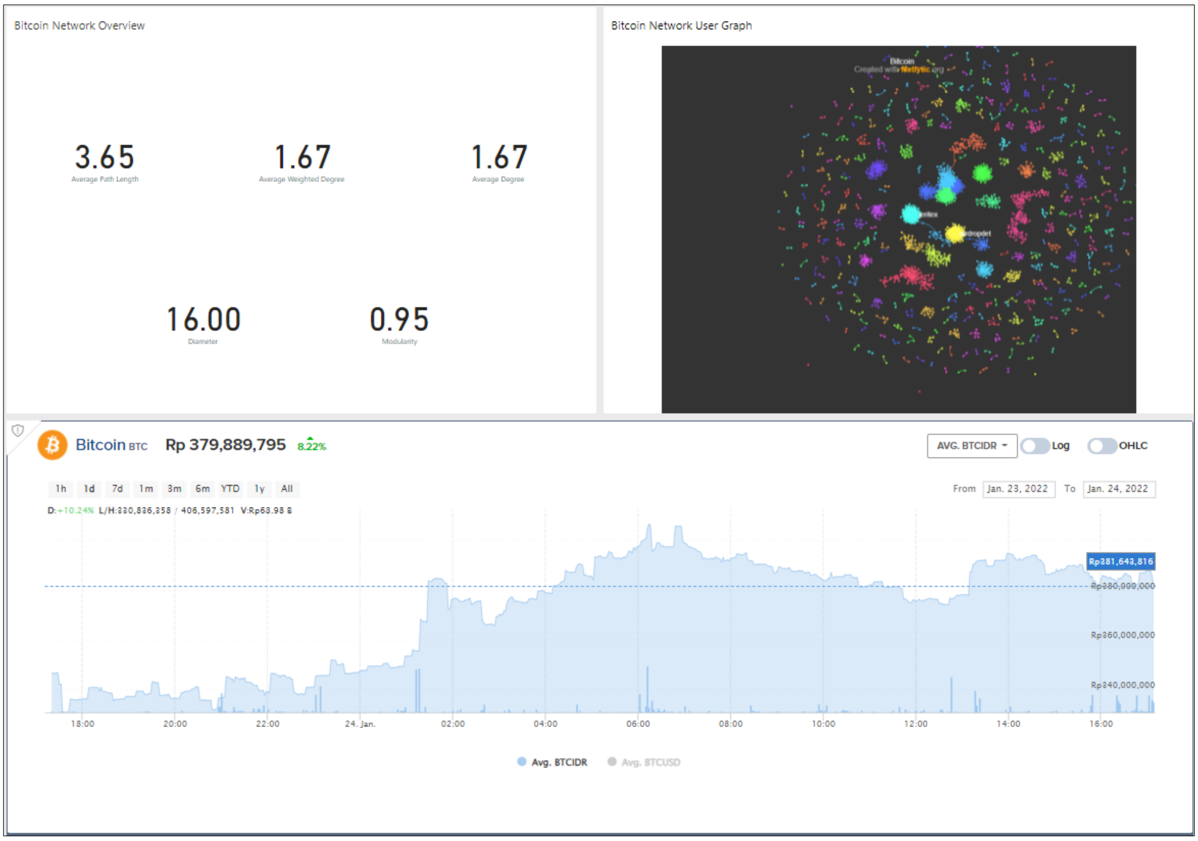

Figure 4(a). Bitcoin's Network Overview

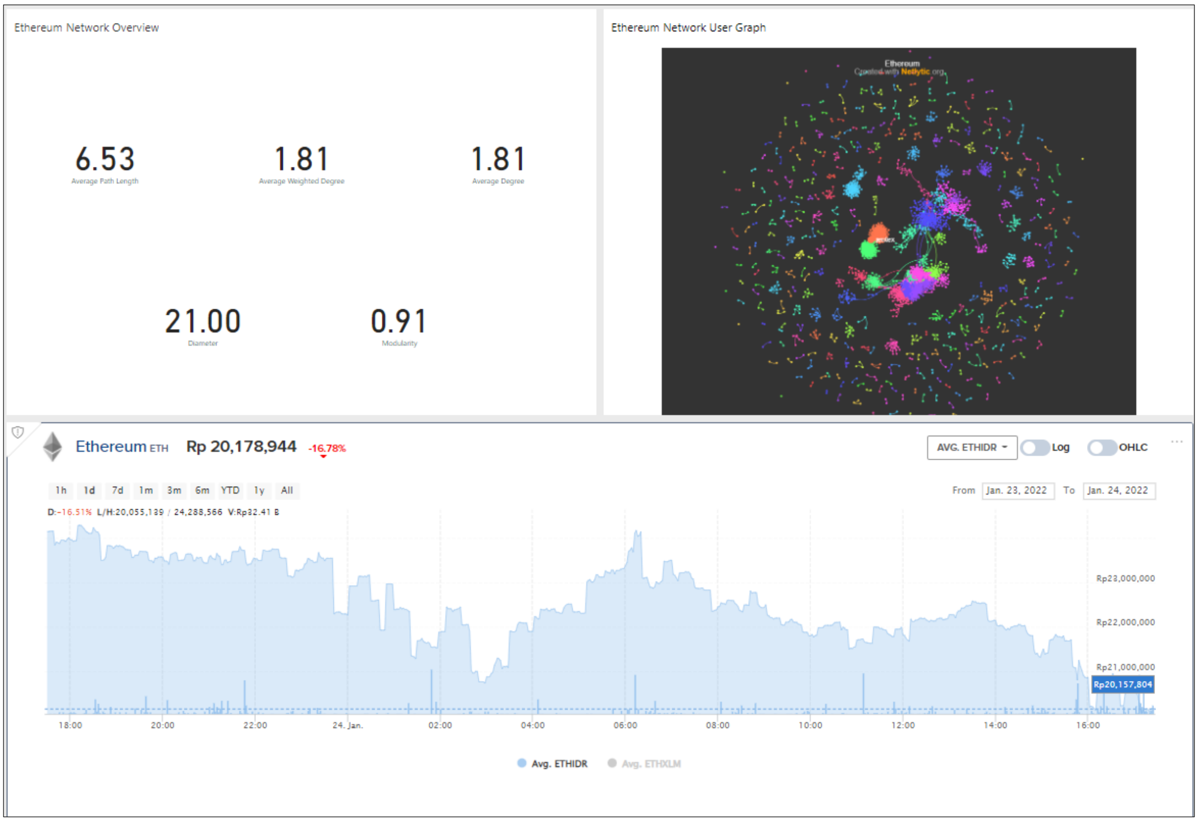

Figure 4(b). Ethereum's Network Overview

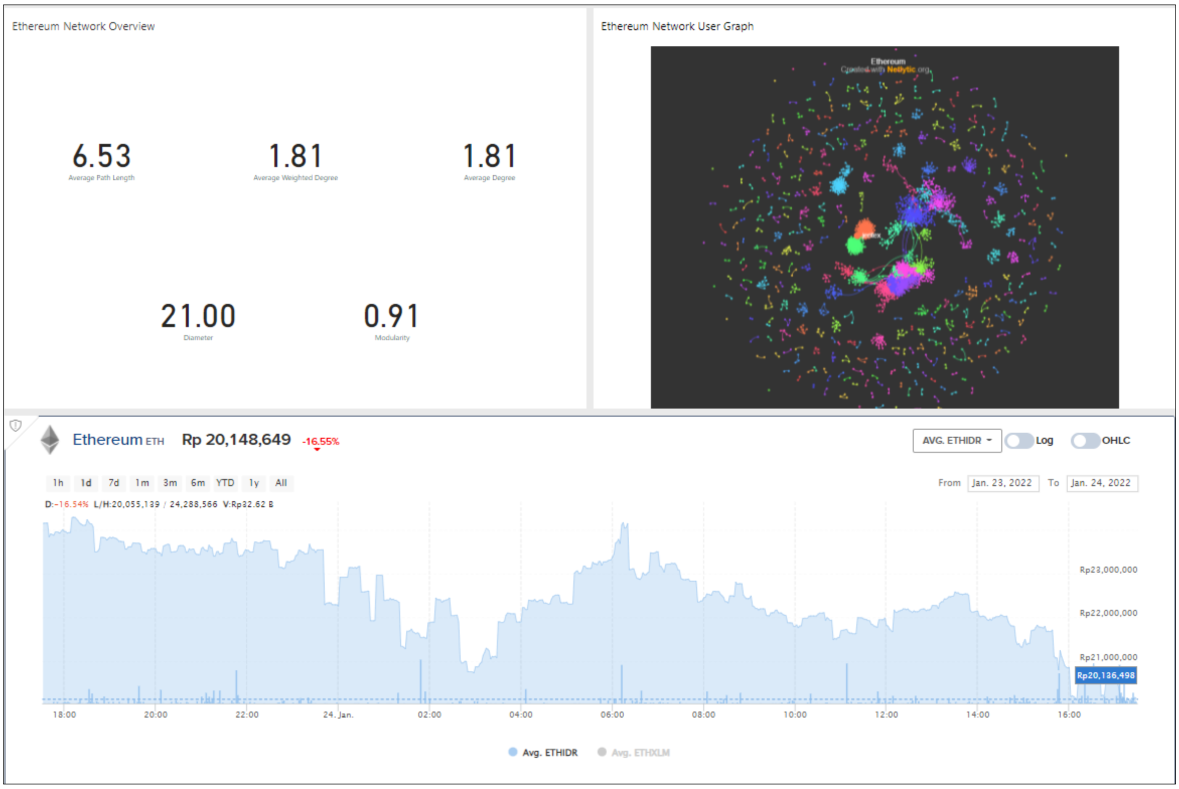

Figure 4(c). Binance Coin's Network Overview

3.2. Cryptocurrencies' Social Network Analysis

The second part of our BI Dashboard contains the comparison between cryptocurrencies' social networks. The comparisons are displayed using graph such as in Figure 5(a), 5(b), 5(c), 5(d), 5(e). For every figure except Figure 5(e), the vertical axis property is the cryptocurrency name, and the horizontal axis presented the SNA value. Meanwhile, in Figure 5(e), the actors are displayed according to their username to see the actors that have the most post on Twitter.

As stated before in the previous sub-section, Binance has the easiest social network and most relation for each actor, but the least interaction in the group because Binance has the highest value of the average *degree*, the smallest value of average *path length*, *diameter*, as well as *modularity*. On the other hand, even though Bitcoin has the smallest value of the average *degree*, Bitcoin has the most interaction in the groups. According to Figure 5(e), multiple actors are involved in every cryptocurrency's social network. This means that they had posted on Twitter using the Twitter keywords which indicates that they are deeply involved in talking about cryptocurrencies on Twitter.

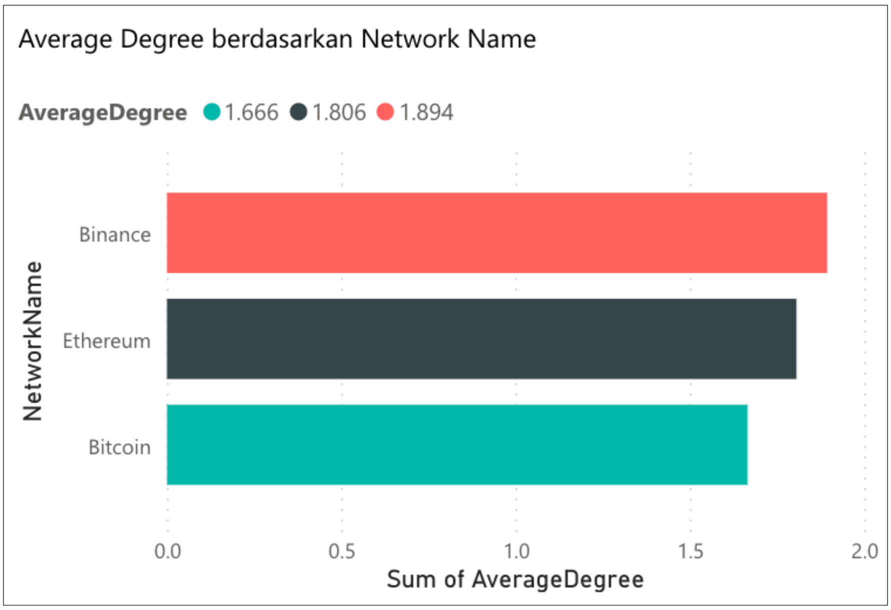

Figure 5(a). Average Degree according to Cryptocurrency Name

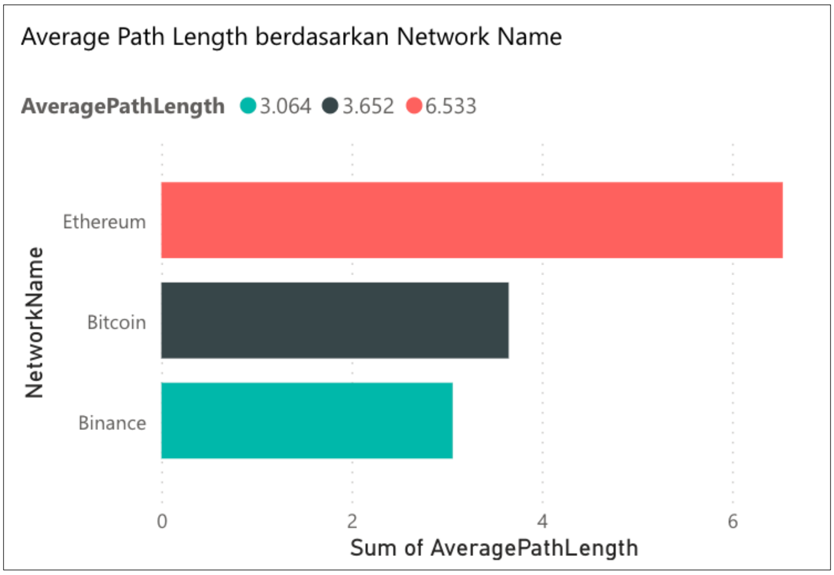

Figure 5(b). Average Path Length according to Cryptocurrency Name

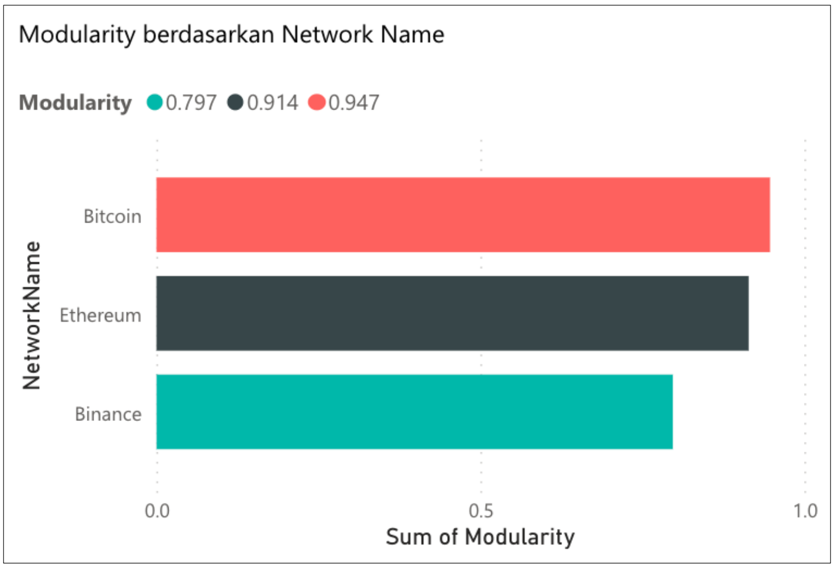

Figure 5(c). Modularity according to Cryptocurrency Name

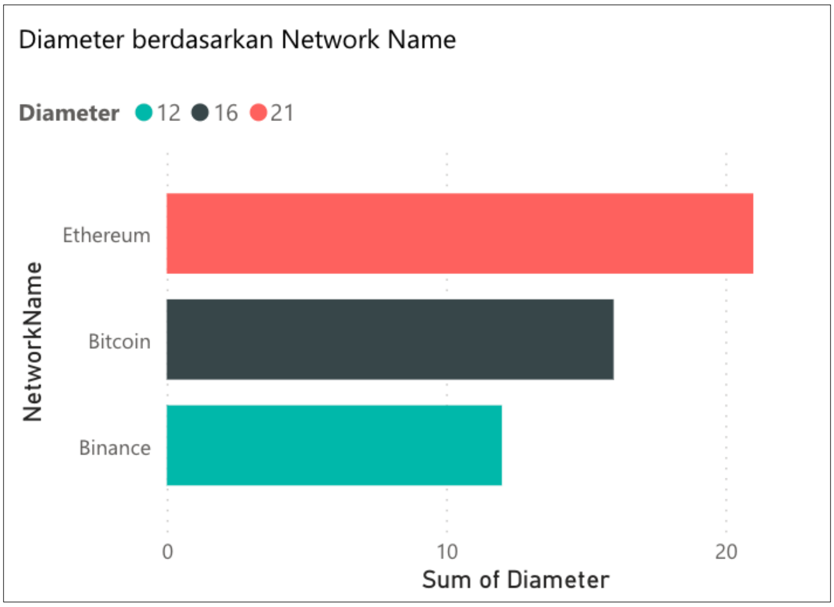

Figure 5(d). Diameter according to Cryptocurrency Name

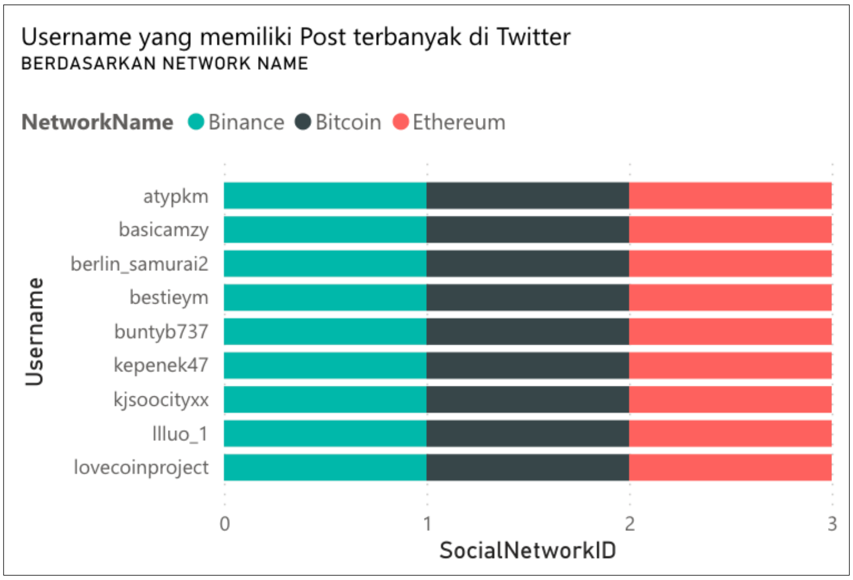

Figure 5(e). Most post by Actors in Twitter

3.3. Cryptocurrencies' Social Network Analysis

Unlike, every actor that posts on Twitter is used to analyze the social network analysis. The donut charts present the top SNA parameter values of actors in each cryptocurrency. As shown in Figure 6(a), around 80% of the cryptocurrencies' social networks are dominated by actors with only one degree or connection. Bitcoin and Ethereum have groups, there is no visibly dominant group, such as group 185 on Binance Coin.

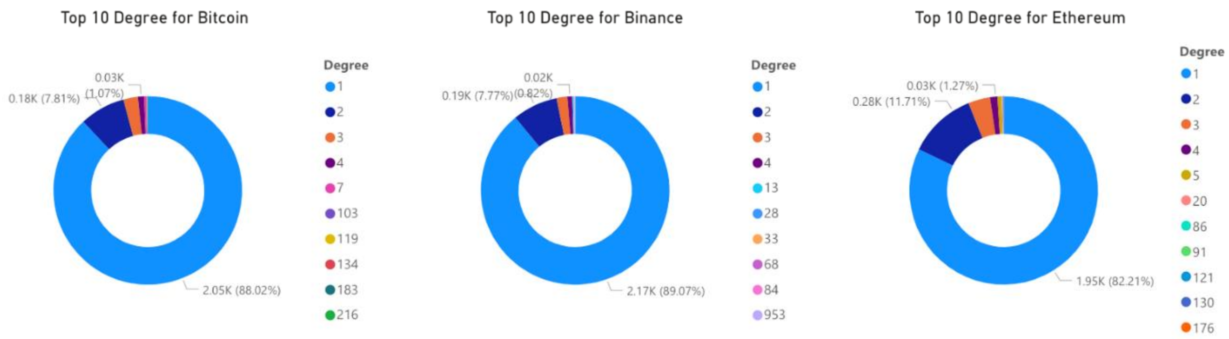

Figure 6(a). Top 10 Degree

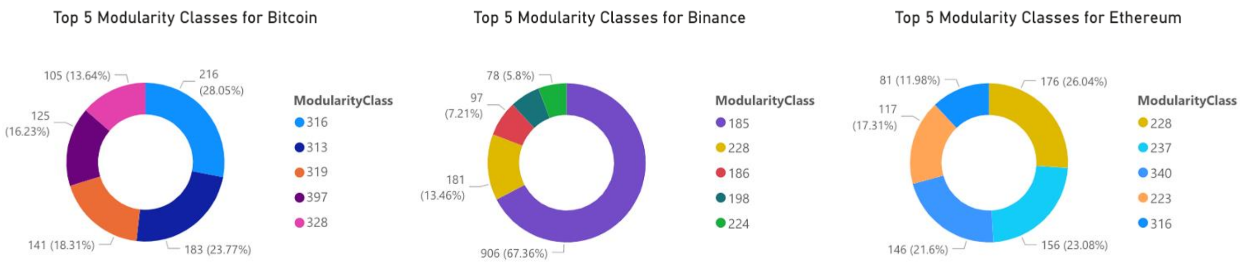

Figure 6(b). Top 5 Modularity Class

4. Conclusion

From the research and study that has been done, Binance has the easiest network for the actors to reach each other (smallest average path length and diameter value) and the highest relation of degree value for each actor or node. Meanwhile, Ethereum's social network is the most difficult for the actors to reach each other because of the biggest average path length and diameter value. Lastly, Bitcoin has the most interaction in the groups, although Bitcoin has the smallest average degree. In every cryptocurrency social network, there are multiple actors that are involved in every cryptocurrency's social network, and around 80 percent of the cryptocurrency social networks are dominated by actors that only have one degree or connection. Based on the statement above, the popularity of cryptocurrencies is influenced by their market price and their actors' activities on social media. Hence, making the decision to buy cryptocurrencies with high popularity on social media should be considered because they tend to retain their value over time and could benefit from price spikes from influential people.

Our conducted research proposed the use of BI Dashboard to present data visualization in the form of graphs, charts, web content, and cards to help us understand the social network analysis data of Binance, Bitcoin, and Ethereum and yet provide facts to make the decision regarding cryptocurrency options between the three easier. This research still uses *the crawling* technique manually, in accordance to provide an opportunity to create an automated data collection or *crawling* process. The use of the BI Dashboard platform other than PowerBI could be more beneficial because there is a limitation regarding the tool, which is the incapability of PowerBI to update the database that is stored locally.

5. Declarations

5.1. Author Contributions

Conceptualization, J.C.S., W.S.S. and A.S.G.; methodology, J.C.S. and W.S.S.; software, J.C.S. and W.S.S.; validation, J.C.S. and W.S.S.; formal analysis, J.C.S. and W.S.S.; investigation, J.C.S. and W.S.S.; resources, J.C.S. and W.S.S.; data curation, J.C.S., W.S.S. and A.S.G.; writing—original draft preparation, J.C.S. and W.S.S.; writing—review and editing, J.C.S., W.S.S. and A.S.G.; visualization, J.C.S. and W.S.S.; supervision, A.S.G.; project administration, J.C.S., W.S.S. and A.S.G.; funding acquisition, J.C.S., W.S.S. and A.S.G.. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

6. References

[1] Wada, H. (2021). Assessing the Social Media User's Credibility Rating of Shared Content, and its Utilization in Decision Making. Emerging Science Journal, 5(2), 191–199. doi:10.28991/esj-2021-01269.

[2] Perrin, A. (2015). Social Media Usage: 2005-2015. In Pew Research Center. Available online: http://www.pewinternet.org/2015/10/08/2015/Social-Networking-Usage-2005-2015/ (accessed on March 2022).

[3] Wątorek, M., Drożdż, S., Kwapień, J., Minati, L., Oświęcimka, P., & Stanuszek, M. (2021). Multiscale characteristics of the emerging global cryptocurrency market. Physics Reports, 901, 1–82. doi:10.1016/j.physrep.2020.10.005.

[4] Nakamoto, S. Bitcoin: A Peer-to-Peer Electronic Cash System. Available online: https://bitcoin.org/bitcoin.pdf (accessed on April 2022).

[5] Rehman, M. H. U., Salah, K., Damiani, E., & Svetinovic, D. (2020). Trust in Blockchain Cryptocurrency Ecosystem. IEEE Transactions on Engineering Management, 67(4), 1196–1212. doi:10.1109/tem.2019.2948861.

[6] Ante, L. (2021). How Elon Musk's twitter activity moves cryptocurrency markets. SSRN Electronic Journal, 1-28. doi:10.2139/ssrn.3778844.

[7] Vidal-Tomás, D. (2021). Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis. Finance Research Letters, 43, 101981. doi:10.1016/j.frl.2021.101981.

[8] Park, S., & Park, H. W. (2019). Diffusion of cryptocurrencies: web traffic and social network attributes as indicators of cryptocurrency performance. Quality & Quantity, 54(1), 297–314. doi:10.1007/s11135-019-00840-6.

[9] Alqassem, I., Rahwan, I., & Svetinovic, D. (2020). The Anti-Social System Properties: Bitcoin Network Data Analysis. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50(1), 21–31. doi:10.1109/tsmc.2018.2883678.

[10] Javarone, M. A., & Wright, C. S. (2018). From Bitcoin to Bitcoin Cash: A network analysis. CRYBLOCK 2018 - Proceedings of the 1st Workshop on Cryptocurrencies and Blockchains for Distributed Systems. doi:10.1145/3211933.3211947.

[11] Aspembitova, A. T., Feng, L., & Chew, L. Y. (2021). Behavioral structure of users in cryptocurrency market. PLOS ONE, 16(1), e0242600. doi:10.1371/journal.pone.0242600.

[12] Pilar, G.-C., Jaureguizar Arellano, D., & Jaureguizar Francés, C. (2018). The cryptocurrency market: A network analysis. ESIC MARKET Economic and Business Journal, 49(3). doi:10.7200/esicm.161.0493.4i.

[13] Sohaib, O., Hussain, W., Asif, M., Ahmad, M., & Mazzara, M. (2020). A PLS-SEM Neural Network Approach for Understanding Cryptocurrency Adoption. IEEE Access, 8, 13138–13150. doi:10.1109/access.2019.2960083.

[14] Biryukov, A., & Tikhomirov, S. (2019). Deanonymization and Linkability of Cryptocurrency Transactions Based on Network Analysis. Proceedings - 4th IEEE European Symposium on Security and Privacy, (EuroS&P). doi:10.1109/eurosp.2019.00022.

[15] Lin, D., Wu, J., Yuan, Q., & Zheng, Z. (2020). T-EDGE: Temporal WEighted MultiDiGraph Embedding for Ethereum Transaction Network Analysis. Frontiers in Physics, 8. doi:10.3389/fphy.2020.00204.

[16] Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. International Review of Financial Analysis, 63, 257–272. doi:10.1016/j.irfa.2018.12.002.

[17] Anticona, P. (2019). Advantages of making a dashboard with a Business Intelligence platform compared to other reporting software. PM World Journal, 8, 1-41.

[18] Camacho, D., Luzón, M. V., & Cambria, E. (2021). New research methods & algorithms in social network analysis. Future Generation Computer Systems, 114, 290–293. doi:10.1016/j.future.2020.08.006.

[19] Valeri, M., & Baggio, R. (2021). Social network analysis: organizational implications in tourism management. International Journal of Organizational Analysis, 29(2), 342–353. doi:10.1108/ijoa-12-2019-1971.

[20] Tabassum, S., Pereira, F. S. F., Fernandes, S., & Gama, J. (2018). Social network analysis: An overview. WIREs Data Mining and Knowledge Discovery, 8(5). doi:10.1002/widm.1256.

[21] Dwi Putra Aditama, T. B., & SN, A. (2020). Determining Community Structure and Modularity in Social Network using Genetic Algorithm. Indonesian Journal of Computing and Cybernetics Systems, 14(3), 219. doi:10.22146/ijccs.57834.

[22] Das, K., Samanta, S., & Pal, M. (2018). Study on centrality measures in social networks: a survey. Social Network Analysis and Mining, 8(1). doi:10.1007/s13278-018-0493-2.

[23] Lee, C.-Y., Chong, H.-Y., Liao, P.-C., & Wang, X. (2018). Critical Review of Social Network Analysis Applications in Complex Project Management. Journal of Management in Engineering, 34(2), 04017061. doi:10.1061/(asce)me.1943-5479.0000579.

[24] Correia, J., Santos, M. Y., Costa, C., & Andrade, C. (2018). Fast Online Analytical Processing for Big Data Warehousing. 2018 International Conference on Intelligent Systems (IS). doi:10.1109/is.2018.8710583.

[25] Negash, S., & Gray, P. (2008). Business Intelligence. Handbook on Decision Support Systems 2, 175–193. doi:10.1007/978-3-540-48716-6_9.

[26] Sun, Z., Sun, L., & Strang, K. (2016). Big Data Analytics Services for Enhancing Business Intelligence. Journal of Computer Information Systems, 58(2), 162–169. doi:10.1080/08874417.2016.1220239.