Stock Market Manipulation Detection using Artificial Intelligence: A Concise Review

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***Abstract*—In the modern era, one of the fundamental trading components of any country is its stock market. Generally, it is the benchmark used to gauge the health of the country's economy. Due to its utmost importance, governments all over the world have set up a set of rigorous regulations to ensure fairness in the trade market. However, there will still be a small group of rogue traders that try to manipulate the stock price through various illegal means. Several popular manipulation schemes such as pump and dump, layering, and quote stuffing are regularly employed to inflate and deflate the stock price artificially without any strong basis. These illegal activities will undermine the integrity of the stock market, which will cause big losses to honest traders. At the moment, a simple rule-based system is used by most of the stock exchange authorities to identify and recognize manipulative cases. More often than not, some of the manipulation cases might be left undetected, especially in the digital era, where the trading volume has increased significantly. Therefore, an automated tool is needed to supplement human operators in identifying and recognizing such manipulation cases. Nevertheless, the complexity of the manipulation strategies has also increased with the help of various automation tools. Hence, several works have explored the application of artificial intelligence technology to detect manipulation cases in the stock market trading automatically. This paper will first provide a brief introduction to stock market manipulation, followed by some literary works on artificial intelligence methods that have been applied to detect manipulation activities in the stock market. Most of the existing works rely on the standard machine learning approach that includes artificial neural networks, support vector machine, random forest, and decision tree classifiers. At the moment, there is no standard public database that can be used to benchmark the effectiveness of the machine learning techniques in detecting the manipulation cases. Each researcher focuses on stock exchange data from their country of origin, either through daily or tick trading data. At the end of this paper, some suggestions are shared for possible future research directions.**

***Index Terms*—Stock Market, Manipulation Detection, Artificial Intelligence, Pump and Dump, Quote Stuffing**

I. Introduction

The manipulation of stock markets has been a topic of growing interest in recent times. It is important to identify these manipulation cases as it hinders the growth, integrity, and stability of the financial markets [1]. Besides that, these illegal activities damage the trust of traders in the stock market [2]. The economics literature has provided significant discussions on how to identify and describe various strategies of stock price manipulation. Jarrow [3] has defined manipulation activity as a trading technique that produces real positive wealth at zero-level of risk. Similarly, Thel [4] pointed out that stock price manipulation is a transaction that is carried out with the intention to decrease or increase the security's reported price. Meanwhile, Cherian and Jarrow [5] described manipulation activity as a trading undertaking of a person or a group of people that try to skew the stock price towards his or their benefit. A more recent study by Baker and Kiymaz [6] explains that stock market manipulation involves various aspects, like trading frequency, trading volume, order size, and stock price fraction magnitude. In general, stock market manipulation is defined as an illegal practice that attempts to raise or lower any stock price by creating an active manipulation trading appearance [7], [8].

Therefore, it is an utmost important task of the regulators to identify and recognize these illegal activities as early as possible. However, due to the advent of the digital era that allows the trading volumes to increase significantly, it is hard to catch these illegal activities manually. Even more, total reliance on human observers is not an optimal practice in term of costing, whereby human is prone to fatigue and subjective in making a decision. Therefore, an automated tool will be a big helping hand in increasing the identification rate of these manipulation activities. Moreover, an intelligent system can also be designed so that the detection results can be inferred at a faster rate. Hence, the core of this intelligent system is the implementation of artificial intelligence (AI) technology in monitoring the fluctuation patterns of the stock price. AI has been successfully applied to various applications that cover from healthcare technology [9], security and safety system

[10] and construction industry [11]. In certain situations, [12], [13], it has even beat human capability in performing several dedicated tasks. To be more precise, the advent of a new deep learning paradigm that produces end-to-end intelligent systems has enabled this big leap advancement [14]. Contrary to this paradigm, the traditional AI utilizes handcrafted feature extraction methods before it is trained either for classification or regression task [15]. In this paper, a brief introduction to stock manipulation will be discussed first, followed by a concise review of state-of-the-art artificial intelligence technology that has been applied in this domain.

II. Stock Market Manipulation

Generally, manipulative stock trading activities can be broadly classified into three categories as proposed by Allen and Gale [16], which are information-based, action-based, and trade-based manipulations. Since then, a large number of works have been published in the literature, focusing on various types of stock market manipulation strategies. According to [16], action-based manipulation is a situation in which there is a deliberate action to affect the value of stocks by any party. An example of such an action is closing a branch by the company's director so that the stock will be traded at a lower price. On the other hand, information-based manipulation is executed by spreading rumors or wrong information about the market with the intention to falsely affect the price of an equity. Contrary to the previous two manipulation strategies, trade-based manipulation does not employ any illegitimate action. It involves fictitious trading by stock market intermediaries with the intention to induce market prices so that it will follow manipulators' expectations. The manipulators will create bid or ask orders, which they aim to immediately cancel before they are executed and hence influencing the closing bid or ask quotes. According to Lee et al. [17], quote stuffing and spoofing trading are the common examples of these manipulative tactics. Quote stuffing involves a series of new orders in the market that are canceled in quick succession to push the price to the new desired bid or ask prices. Each of these new prices is then used as bait to incite the opposing order, which will result in profits to the manipulators. Meanwhile, spoofing trading is executed by creating orders with large volumes but at a moderate pricing mark.

Aggarwal and Wu [18] carried on from the previous work, whereby they examined the cases of trade-based manipulation in the United States of America (USA). This type of manipulation is also known as the 'pump and dump' strategy. It starts with a set of pumping schemes, in which the manipulators create a cartel to buy the stocks collectively so that the demand will be falsely inflated and drive the stock's price up artificially. This artificial surge in the pricing and trading volume patterns attracts uninformed traders who might follow suit and buy the stock in a greater bulk due to the deceiving activities. When the manipulators feel that the stocks have been significantly overvalued, they will quit the market by selling their shares at a substantially higher price compared to the buying price and hence, accrued an excessive profit. As a consequence, there will be a sheer decline in buying volume once the manipulators exit the market, which will then drive down steeply the stock price. Once again, this abrupt situation will create deceiving signals to the uninformed traders who might try to reduce their loss or save whatever little amount of their investment is left with. This mitigative action will create another chance for the manipulators to reap another round of profit by repurchasing the stocks at much lower prices [2], [19]. Aggarwal and Wu [18] have studied 51 manipulations cases that occur throughout 1990 up to 2001, which they concluded that a stock price generally rises during the pre-manipulation phase and decreases during the post-manipulation phase. They also found out that equities with low values and illiquidity are commonly targeted. Similarly, Huang and Cheng [20] examined the pump and dump manipulation cases in Taiwan and concluded that these manipulation activities will lead to market inefficiency and higher uncertainty.

Another group of researchers has investigated the relationship between market manipulation and the closing prices of stocks. Kumar and Seppi [21] applied the framework proposed by Kyle [22] in order to model manipulator actions who buy a significant portion of future market securities and actively attempt to raise the spot prices before the closing for the sake of making money from a much desirable closing price of futures. In Hillion and Suominen [23] framework, brokers manipulate the closing price of a stock with the aim to portray a better impression of their execution quality to their customers. A more recent framework relating to investment decisions of mutual fund managers as introduced by Bernhardt and Davies [24] suggested that managers were given incentives for manipulating stock prices at the closing reporting period. These studies prove that manipulation cases can also occur because of the agency policy.

Theoretical and empirical studies that discuss the detection of stock market manipulation activities are not in short supply. Many of these works have focused on the changes of certain market variables during post-manipulation and pre-manipulation periods such as transaction price, volume, liquidity, and volatilities [25]–[28]. For example, Ogut et al. [25] have developed several methods to detect manipulation cases for the Istanbul Stock Exchange. They found, among other things, that machine learning techniques such as Artificial Neural Networks (ANN) and Support Vector Machine (SVM) can be used to detect stock-price manipulation. Diaz et al. [26] offered empirical evidence of stock manipulation in the USA market by incorporating the analysis of intraday trade prices using knowledge discovery techniques. The study reveals that a high presence of returns, volatility, and volume outliers is directly related to the manipulation activities. The results in Cao et al. [27] claim to show that their computational Markov model intelligence approach can better detect manipulations or anomalies in the bid and ask prices on NASDAQ and the London Stock Exchange over other benchmark models. The proposed models have been tested on both real-life stock prices and simulated prices. Using the actual tick data of

US stocks, Zhai et al. [28] further argued that while the change in the market variables had important roles in detecting manipulation cases, there is no solid proof that the change in the market is a sufficient condition to identify them. They further argued that those changes could probably be the results of other events in the market. Therefore, in their study, they showed that their proposed new data analytic approach i.e. the combination of static and dynamic models is able to detect market manipulations purely based on manipulative behaviors, not just due to changes in the market variables. They have also proven that their method works better than other selected benchmark models.

In light of the current state of the literature on stock market manipulations, few studies have designed stock market manipulation detectors through artificial intelligence (AI) by analyzing the trading behavior data. As this technology is getting more advanced, manipulation strategies are becoming more complex from day to day. Moreover, data analytic methods have been intensively applied in the field of finance to improve analytical performance of daily forecasting of stock returns and portfolio management [29], [30]. Therefore, several AI techniques that have been applied to detect the occurrence of stock market manipulation activities will be discussed in the next section.

III. Artificial Intelligence Applications in Stock Market Manipulation Detection

Artificial intelligence or its subset field, machine learning has been successfully applied in the finance industry to automate various decision-making. An example of such an application is credit card fraud detection system [31] that is used to identify unauthorized transactions using several machine learning techniques. These techniques were fine-tuned to learn the unauthorized transaction patterns using supervised algorithms that include logistic regression (LR), random forest (RF), and support vector machine (SVM). Since the methodology is based on supervised techniques, the eight streams of input data will be mapped to a dual-class output with annotated labels to recognize the fraud cases. Similarly, there are several works [32]–[34] that have been dedicated to the detection of manipulation cases in the stock market transactions using AI. One of the basic modeling methods that have been used in identifying stock market manipulation cases is agent-based modeling, which utilizes two normal distribution models to simulate the cases with and without price manipulator interference, respectively. They have used an intra-day stock data format, which was divided into six equal parts. The buyer and seller were categorized into six classes with three distinct class representations for each of them. They have argued that the manipulator behavior will follow a pattern of immediate purchasing at the best existing price. Hence, they will be a skewness in the manipulator modeling, which is then used to identify the manipulation cases.

The previous method does not apply any recursive learning procedure as the model parameters were determined by the model designer. Contrary to that, Uslu and Akal [32] have implemented several AI techniques, in which the parameters were recursively updated to reach optimal modeling configurations to identify manipulation cases in trade-based of the capital market instrument. Borsa Istanbul stock data was used as the testbed with 22 cases of trade manipulation. They have made sure that the data of non-manipulated cases is twice bigger than the manipulated cases. The ground truth is annotated by assigning a high-class label to the whole period of manipulation trading, while a low-class label for pre and post manipulation periods. Six classification methods have been tested that include LR, RF, SVM, decision tree (DT), K-nearest neighbor (KNN), and Naive Bayes (NB) classifiers using three types of input features, which are weighted average price, minimum price, and maximum price. Based on their conclusion, NB returned the best performance on average with the highest F1-score of 0.85. A unique method has been devised by Madurawe et al. [34] for analyzing manipulation cases based on collusion scheme through clustering method. They have implemented an unsupervised methodology that will first cluster the possible groups of buyers and sellers, which was used to infer the possibility of collusion using graph clustering methods. It is a challenging task, whereby a bigger group of buyers or sellers can very much mimic the normal trading activities compared to the manipulation attempt by a single entity. The authors have pre-configured several parameters such as the number of collusive groups, the maximum number of investors per group, collusion intensity, and collusion period to boost the clustering performance. Four AI techniques have been implemented, and the combination of optics clustering and local outlier forest classifier produced the best collusion set detection with an average sensitivity of 0.886.

Rather than focusing on identifying the manipulation cases, Mizuta [35] have created an AI-Bot to executed the manipulation case itself. It is important to simulate the manipulation cases so that the regulators can identify any loophole in the current regulations to prevent the possibility of manipulation cases. He has utilized an agent-based approach, embedded with a genetic algorithm to optimized the simulation strategy. The trading volume is limited to be less than 600 with most cases fall under over-buying and under-buying manipulation strategies. Even though only 11 simulations have been explored and vetted, the AI-Bot still managed to come to a conclusion that manipulation-based strategy indeed returns the highest profit. Hence, the author has urged the regulator to tighten the usage of AI in stock trading. Another AI-Bot technique has been proposed by Yagemann et al. [36], in which they have created a Bot2Stock to mimic the manipulation cases. They have focused more on the deterministic patterns of the manipulation trade, rather than the statistical sides. Two manipulation strategies were explored, which are pump & dump and layering. The layering scheme was embedded into the AI-Bot by avoiding imbalance trade activities between ask and bid during the opening order. While for pump & dump, a coordination strategy between AI-Bots is needed, as such the main AI-Bot will not place a bid until the secondary

AI-Bots have pumped up the price. This is done with the intention to avoid trade suspicion during the price pumping stage. One of the best countries with an AI adoption rate is China, which ranks second in the world, right after the USA. A team of researchers [37] have analyzed stock data from China Securities Regulation Commission to recognize the manipulation activities. They have devised several machine learning techniques based on daily and tick trading data, in which they have concurred that daily trading data produced a better detection rate compared to the tick data. K-fold data division was used to avoid bias in data selection and it has been applied to all tested methods that include KNN, SVM, DT, LR, artificial neural networks (ANN), linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA). Surprisingly, the simplest method, KNN produced the best detection rate and this finding might be a consequence of a low number of data with just 64 sets. Besides that, LR produced the lowest detection rate due to the inability of logistic function to model the manipulation cases effectively as proven by its low area under the curve for receiving operating characteristics graph.

Researchers in [38] have also implemented almost the same set of AI algorithms that include KNN, LDA, QDA, LR, and DT classifiers to identify manipulative trades in the Russian stock market. They suggested that there are three generations of AI in the stock market detection, started with the correlation analysis era, followed by KNN related techniques, and continued with an SVM-based approach. Even though it was published in 2018, the authors have not touched upon the deep learning era for stock market manipulation detection. They have focused on identifying two types of manipulation schemes, which are pinging and spoofing. It is an interesting testbed due to the contraction trend in the market size, contrary to the global market that has actually doubled its size. Once again, the simplest method of using KNN returned the best detection rate, which is a similar trend found in [37]. This performance trend is also supported by Kasgari et al.'s research [39], in which they have used simple binary regression and logit model to recognize fraud trading in the Iranian stock market. They have divided the fraud strategies into two broad classes of demand-side manipulation and supply-side of manipulation. They have proposed a composite of four features to alert the possibility of manipulation cases through bilateral trade price change, price changes from the previous day, the ratio of trade basket, and price changes from the previous trade. They have used a five-year period of data from the Tehran Stock Exchange with 4600 rows of data. The proposed method concluded that the ratio of trade basket does not contribute significantly to the detection performance and hence, this feature can be dropped from the model.

The method in [40] suggested a unique pre-processing method before an AI method is used to identify the manipulation cases. This step is important in the traditional machine learning setting, whereby the set of features will be handcrafted and selected by the designer. The author has used stock price, trade volume and bid-ask spread as the input variables to the model, which is then converted to frequency representation using wavelet transformation before dimensionality reduction is performed. Two methods were explored; principal component analysis and factor analysis to reduce the size of input features. Tick data was used instead of the daily trading data with 15 case studies have been tested and verified. Three classifiers were fine-tuned that include XGBoost, KNN, and SVM with XGBoost returned the best detection accuracy performance of 97.78%. All of the previously mentioned methods do not employ any ensemble scheme that is built upon the combination of several weak classifiers, which will be integrated into a strong classifier. On this account, Sridhar et al. [41] have combined several weak classifiers to form a strong model to identify stock market manipulation cases. The proposed algorithm was tested on stock data in the form of daily trading data from the Bombay Stock Exchange, provided by Securities and Exchange Boards of India. They have processed the data into three categories of the pre-manipulation period, the investigation period (period where the manipulation occurs), and the post-manipulation period. They have used 20 types of input attributes and five distinct neural networks as the base model, which will be combined using a weighted average scheme. Several other traditional machine learning techniques that include KNN, ANN, LR, NB, SVM, LDA, and QDA were also tested as benchmark comparisons. They found out that an ensemble of NN classifiers has managed to increase the detection performance over a singular NN classifier from 88% to 96%.

IV. Conclusion

In conclusion, AI has been successfully applied to detect and identify manipulation cases in the stock market. The majority of the approaches have utilized tick data in their experiments, rather than daily trading data. In general, the price pattern in tick data is more likely to be influenced by the outliers compared to the daily trading data. Apart from that, most of the existing methods were based on the traditional machine learning paradigm, which requires the model designer to select the optimal set of features as the input variables. SVM classifier is the most popular method where it has been used as the proposed method or for the benchmarking purpose. Besides that, it is interesting to note that several works have reported that the simplest tested classifier produces the best detection rate. This finding might corroborate with the low numbers of testing data in verifying the algorithm performance. Moreover, there is no publicly available online dataset that can be used as the general benchmark since most researchers have used their own country's stock data to verify their proposed methods. As for future work, deep learning analysis that includes a dense feedforward model [42] can also be explored to mitigate the lack of data so that a more complex relationship can be mapped to extract meaningful patterns of existing and new manipulation strategies. Apart from that, it is also important to explore and improve the network security of the stock market.

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References

[1] W. Aussenegg, R. Jelic, and R. Ranzi, "Corporate insider trading in europe," *Journal of International Financial Markets, Institutions and Money*, vol. 54, pp. 27–42, 2018.

[2] A. S. Azad, S. Azmat, V. Fang, and P. Edirisuriya, "Unchecked manipulations, price–volume relationship and market efficiency: Evidence from emerging markets," *Research in International Business and Finance*, vol. 30, pp. 51–71, 2014.

[3] R. A. Jarrow, "Market manipulation, bubbles, corners, and short squeezes," *Journal of financial and Quantitative Analysis*, vol. 27, no. 3, pp. 311–336, 1992.

[4] S. Thel, "$850,000 in six minutes-the mechanics of securities manipulation," *Cornell L. Rev.*, vol. 79, p. 219, 1993.

[5] J. A. Cherian and R. A. Jarrow, "Market manipulation," *Handbooks in Operations Research and Management Science*, vol. 9, pp. 611–630, 1995.

[6] H. K. Baker and H. Kiymaz, *Market Microstructure in Emerging and Developed Markets: Price Discovery, Information Flows, and Transaction Costs*. John Wiley and Sons, 2013.

[7] A. Riyanto and Z. Arifin, "Pump-dump manipulation analysis: the influence of market capitalization and its impact on stock price volatility at indonesia stock exchange," *Review of Integrative Business and Economics Research*, vol. 7, pp. 129–142, 2018.

[8] T. Akram, S. A. RamaKrishnan, and M. Naveed, "Assessing four decades of global research studies on stock market manipulations: a sceintometric analysis," *Journal of Financial Crime*, 2021.

[9] M. A. Zulkifley, S. R. Abdani, and N. H. Zulkifley, "Pterygium-net: A deep learning approach to pterygium detection and localization," *Multimedia Tools and Applications*, 2019.

[10] I. Jung, J. Son, M. Baek, and B. Han, "Real-time mdnet," *CoRR*, vol. abs/1808.08834, 2018. [Online]. Available: http://arxiv.org/abs/1808.08834

[11] S. M. Mitu, N. A. Rahman, K. A. M. Nayan, M. A. Zulkifley, and S. A. P. Rosyidi, "Implementation of machine learning algorithms in spectral analysis of surface waves (sasw) inversion," *Applied Sciences*, vol. 11, no. 6, p. 2557, 2021.

[12] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, "Imagenet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, no. 3, pp. 211–252, Dec 2015.

[13] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, N. Navab, J. Hornegger, W. M. Wells, and A. F. Frangi, Eds. Cham: Springer International Publishing, 2015, pp. 234–241.

[14] S. R. Abdani, M. A. Zulkifley, and N. H. Zulkifley, "Group and shuffle convolutional neural networks with pyramid pooling module for automated pterygium segmentation," *Diagnostics*, vol. 11, no. 6, p. 1104, 2021.

[15] M. A. Zulkifley, M. M. Mustafa, A. Hussain, A. Mustapha, and S. Ramli, "Robust identification of polyethylene terephthalate (pet) plastics through bayesian decision," *PloS one*, vol. 9, no. 12, p. e114518, 2014.

[16] F. Allen and D. Gale, "Stock-price manipulation," *The Review of Financial Studies*, vol. 5, no. 3, pp. 503–529, 1992.

[17] E. J. Lee, K. S. Eom, and K. S. Park, "Microstructure-based manipulation: Strategic behavior and performance of spoofing traders," *Journal of Financial Markets*, vol. 16, no. 2, pp. 227–252, 2013.

[18] R. K. Aggarwal and G. Wu, "Stock market manipulations," *The Journal of Business*, vol. 79, no. 4, pp. 1915–1953, 2006.

[19] S. Neupane, S. G. Rhee, K. Vithanage, and M. Veeraraghavan, "Trade-based manipulation: Beyond the prosecuted cases," *Journal of corporate finance*, vol. 42, pp. 115–130, 2017.

[20] Y. C. Huang and Y. J. Cheng, "Stock manipulation and its effects: pump and dump versus stabilization," *Review of Quantitative Finance and Accounting*, vol. 44, no. 4, pp. 791–815, 2015.

[21] P. Kumar and D. J. Seppi, "Futures manipulation with "cash settlement"," *The Journal of Finance*, vol. 47, no. 4, pp. 1485–1502, 1992.

[22] A. S. Kyle, "Continuous auctions and insider trading," *Econometrica: Journal of the Econometric Society*, pp. 1315–1335, 1985.

[23] P. Hillion and M. Suominen, "The manipulation of closing prices," *Journal of Financial Markets*, vol. 7, no. 4, pp. 351–375, 2004.

[24] D. Bernhardt and R. J. Davies, "Smart fund managers? stupid money?" *Canadian Journal of Economics/Revue canadienne d'économique*, vol. 42, no. 2, pp. 719–748, 2009.

[25] H. Öğüt, M. M. Doğanay, and R. Aktaş, "Detecting stock-price manipulation in an emerging market: The case of turkey," *Expert Systems with Applications*, vol. 36, no. 9, pp. 11 944–11 949, 2009.

[26] D. Diaz, B. Theodoulidis, and P. Sampaio, "Analysis of stock market manipulations using knowledge discovery techniques applied to intraday trade prices," *Expert Systems with Applications*, vol. 38, no. 10, pp. 12 757–12 771, 2011.

[27] Y. Cao, Y. Li, S. Coleman, A. Belatreche, and T. M. McGinnity, "Adaptive hidden markov model with anomaly states for price manipulation detection," *IEEE transactions on neural networks and learning systems*, vol. 26, no. 2, pp. 318–330, 2014.

[28] J. Zhai, Y. Cao, and X. Ding, "Data analytic approach for manipulation detection in stock market," *Review of Quantitative Finance and Accounting*, vol. 50, no. 3, pp. 897–932, 2018.

[29] A. Oztekin, R. Kizilaslan, S. Freund, and A. Iseri, "A data analytic approach to forecasting daily stock returns in an emerging market," *European Journal of Operational Research*, vol. 253, no. 3, pp. 697–710, 2016.

[30] R. Mendes, A. Paiva, R. S. Peruchi, P. P. Balestrassi, R. C. Leme, and M. Silva, "Multiobjective portfolio optimization of arma–garch time series based on experimental designs," *Computers & Operations Research*, vol. 66, pp. 434–444, 2016.

[31] Y. Kumar, S. Saini, and R. Payal, "Comparative analysis for fraud detection using logistic regression, random forest and support vector machine," *Random Forest and Support Vector Machine (October 18, 2020)*, 2020.

[32] N. C. Uslu and F. Akal, "A machine learning approach to detection of trade-based manipulations in borsa istanbul," *Computational Economics*, pp. 1–21, 2021.

[33] M. Zare, O. Naghshineh A, E. Salavati, and A. Mohammadpour, "An agent-based model and detect price manipulation based on intraday transaction data with simulation," *Applied Economics*, pp. 1–19, 2021.

[34] R. N. Madurawe, B. I. Jayaweera, T. D. Jayawickrama, I. Perera, and R. Withanawasam, "Collusion set detection within the stock market using graph clustering & anomaly detection," 2021.

[35] T. Mizuta, "Can an ai perform market manipulation at its own discretion?–a genetic algorithm learns in an artificial market simulation–," in *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, 2020, pp. 407–412.

[36] C. Yagemann, S. P. Chung, E. Uzun, S. Ragam, B. Saltaformaggio, and W. Lee, "On the feasibility of automating stock market manipulation," in *Annual Computer Security Applications Conference*, 2020, pp. 277–290.

[37] A. Li, J. Wu, and Z. Liu, "Market manipulation detection based on classification methods," *Procedia Computer Science*, vol. 122, pp. 788–795, 2017.

[38] A. Zaborovskaya, V. Zaborovskiy, and K. Pletnev, "Possibilities of preventing manipulative transactions on the stock market in the conditions of new industrialization," in *2nd Int. Scientific Conf. on New Industrialization: Global, National, Regional Dimension (SICNI 2018)*, 2019, pp. 154–160.

[39] A. B. Kasgari, M. T. Taghavifard, and S. G. Kharazi, "Price manipulation fraud detection by intelligent visual fraud surveillance system," in *2019 6th International Conference on Control, Decision and Information Technologies (CoDIT)*. IEEE, 2019, pp. 1646–1651.

[40] S. Youssef, "Stock market manipulation detection using continuous wavelettransform and machine learning classifification," Master's thesis, American University in Cairo, 2021.

[41] S. Sridhar, S. Mootha, and S. Subramanian, "Detection of market manipulation using ensemble neural networks," in *2020 International Conference on Intelligent Systems and Computer Vision (ISCV)*. IEEE, 2020, pp. 1–8.

[42] S. R. Abdani and M. A. Zulkifley, "Densenet with spatial pyramid pooling for industrial oil palm plantation detection," in *International Conference on Mechatronics, Robotics and Systems Engineering*, 2019.