**Educational Administration: Theory and Practice**
2024,30(4), 203-209
ISSN:2148-2403
https://kuey.net/

**Research Article**

# Implementation Of An Artificial Intelligence And Machine Learning Powered Financial Decision-Support System For Stock Market Speculators

Indranil Bandyopadhyay*

*Professor, Department of Management and Social science, Haldia Institute of Technology, ibanerjee2000@gmail.com

**Citation:** Indranil Bandyopadhyay et al., Implementation Of An Artificial Intelligence And Machine Learning Powered Financial Decision-Support System For Stock Market Speculators, *Educational Administration: Theory And Practice*, *30*(4), 203-209,
Doi: 10.53555/kuey.v30i4.1433

**ARTICLE INFO**

**ABSTRACT**

A chaotic, non-stationary, and intricate system, the stock market is always changing. A large number of people find value in this investing platform. The stock market is still a great place to make money, but investors are wary of it because of the inherent uncertainty in the banking sector and a number of other factors.Many several aspects that often pass unnoticed by innocent investors. If you want to succeed in the stock market, you need to be able to focus on the here and now while also giving some thought to how today's events may affect tomorrow. As a result, many investors encounter the possibility of failure every day. The current situation calls for a Decision Support System (DSS) that can determine the optimal time to buy stocks and which stocks to buy based on market trends, financial research, and strategy.To help individual investors make informed stock market purchases and sales, this study proposes the creation of an AI-based decision support system (DSS). To remove the behavioral biases inherent in human decision-making and to provide reasonably accurate long-term stock price predictions, the financial decision-support system must be based on mathematical modeling of the different financial characteristics. In this study, we primarily examined the use of two Machine Learning Models: Linear Regression and Artificial Neural Networks (ANNs). We discovered that ANNs outperform Linear Regression in terms of accuracy because of their capacity to produce non-linear outputs. Additionally, we discovered that ANNs are better suited for deep learning applications, as they can solve complicated financial regression problems using their multiple hidden layers. Neural networks powered by artificial intelligence (AI) have the potential to transform the way people make investing and financial decisions in almost every way.

**Keywords—** Decision Support Systems (DSS), Stock Markets, Artificial Intelligence (AI), Machine Learning (ML), Mathematical Modeling (MM)

## INTRODUCTION

Many individual investors are actively involved in stock trading activities, thanks to advancements in information technology, computing infrastructure, and online trading systems. The stock markets are one of the leading investment opportunity avenues accessible to millions of investors worldwide.[1] A big financial choice for individual investors looking to outperform other financial instruments with their hard-earned money is to invest in the stock markets. Those who want to put their money into the stock market should be well-versed in the dangers associated with evaluating stocks based on their technical and fundamental characteristics. Most people who put their money into the stock market have no idea what they're doing or have no idea how to choose stocks because of how complicated the industry is. It is not feasible for many segments of the global investing community to employ investment advisers capable of managing their stock market assets. Because they have made poor choices without weighing the potential benefits and risks, these financial advisers' credibility has been called into doubt on several occasions.[2][3] Many inexperienced investors have met their financial demise because of the many inaccurate stock price prediction services offered by financial guidance websites. According to the researcher, given these facts, it is necessary to have an Automated Decision Support System that can automatically determine the correlation between stock fundamentals and price, conduct in-depth analyses, and build a portfolio of high-performing premium stocks to spread out risk and increase returns. Modern banking, payment processing, internet trading, foreign exchange, and many other financial services rely heavily on computerized technology. There are a lot of algorithmic trading systems that rely on complicated mathematical models, and a lot of them use AI and ML to spot fraudulent financial transactions and forecast the stock market. These platforms are revealing a lot about the future of the financial industry and are already having a major effect on how it operates.[4]

Machine learning, a subfield of AI, is revolutionizing several industries, including the banking sector. Machine learning systems are able to tackle difficult issues by analyzing historical data and drawing conclusions. A subfield of AI known as decision support systems, these tools help users through difficult decision-making processes and, in many instances, do it entirely automatically.[5] Domains like the financial industry, which deals with massive amounts of data that need quantitative analysis in order to make rapid choices on investments, trading, payments, and related topics, are ideal for these kinds of systems. This study's overarching goal is to build a Financial Decision Support System (DSS) that can reliably (>80%) determine the correlation between key financial metrics and stock prices, run automated (within reasonable margins of error) analyses of stock health and risk, and generate superior returns than the market average by selecting a portfolio of high-performing stocks.[6] The Financial DSS is built on a Hybrid DSS architecture that combines several models into one. One model uses AI and ML to predict stock prices. Another model uses mathematics to determine the stock's intrinsic value. Finally, there's a model that measures the stock's overall financial health using quantitative financial variables.[7] We will choose the best performing model by evaluating several AI/ML algorithms on their ability to forecast stock prices. The suggested model for intrinsic value computation in this research is based on the stock life cycle. It dynamically examines profits and growth rates for each phase, much like a real-life firm would. As a result, the model accurately mimics the ups and downs of the real world. The financial health analysis model is built on key financial ratios of each stock and thoroughly examines not only its earnings but also its short-term and long-term debt, revenue and profitability growth rates, peer comparison, and intrinsic analysis.[8][9] When building a portfolio, the algorithm takes into account the equities with the highest health ratings. According to our research, this study's proposed financial DSS is the first of its kind since it integrates three separate models—the AI/ML stock price model, the Intrinsic Value mathematical model, and the Comprehensive stock health analysis model—to determine which stocks will have the best return on investment and to generate automated stock recommendations[10]. The most consequential area of study within financial economics is financial decision-making. When it comes to the growth and longevity of the global economic system, the study of financial decision-making ranks among the various subfields that fall under the umbrella of social sciences.[11]

Decisions in the financial sector, like those in other social sciences, rely heavily on anecdotal evidence. Statistical inference based on models is the gold standard in financial econometrics. Despite econometrics' centrality to other branches of economics, financial decision-making is distinct due to the centrality of uncertainty in both theory and practice.[12]

Human intellect and gut feelings, which are part of Behavioral Finance, are still crucial to financial decision-making. Business Intelligence (BI) and management information systems (MIS) based systems helps in risk assessment and reward estimate, however this is still not enough to improve decision-making processes.[13][14]

Data mining and business intelligence have gone a long way, but there are still a lot of blunders that go into decision-making, and bad financial decisions cost stakeholders a lot of money. Business intelligence and management information systems (BI/MIS) fail in the financial arena because they are based on complicated sets of preprogrammed rules that lack situational awareness and the capacity to adapt to changing ground realities. This results in decisions that are not well-informed.[15]

There isn't yet an algorithm in the financial sector that can evaluate massive volumes of historical data, adjust to real-world changes, and make autonomous decisions based on accurate risk-reward analyses in the same way that humans can.A branch of artificial intelligence, machine learning enables computers to "learn" new tasks and improve at them over time without any help from humans or explicit programming.[16]

Machine learning seeks to develop programs with the ability to learn from data without human intervention.

This research presents the idea of an artificial intelligence (AI) decision support system (DSS) to aid individual investors in making educated stock market transactions. Financial decision-support systems that rely on mathematical modeling of many financial aspects may eliminate human decision-making biases and provide relatively accurate long-term stock price forecasts. We propose a novel approach that, by use of mathematical models and AI/ML, takes into account the stock's intrinsic value as well as the external factors influencing its price. A detailed description of the model and machine learning approaches that would work well with this kind of system is provided. We discuss the external macroeconomic factors that affect the stock price and the particular features that work for calculating the stock's intrinsic value in the paper's subsequent portions. We conclude by outlining the Financial DSS's long-term objectives and development responsibilities and discussing the potential advantages of having one for individual investors..

### Stock Price Prediction and Its Genesis - Efficient Market Hypothesis

The two primary traditional methods that are used in the process of forecasting stock prices are known as fundamental analysis and technical analysis. Both methods provide predictions about stock prices, but they do it in distinct ways.[17] The only data items that are used in technical analysis are the stock price data, the transaction volume, and the intraday changes. There are three financial statements that serve as the foundation of fundamental analysis: the profit and loss statement, the balance sheet, and the cash flow statement. Studying the research that has been done on these two renowned stock prediction systems is something that the researcher is interested in doing so that they may understand about the benefits and drawbacks of these systems. The underlying proof that stock prediction is a feasible alternative is provided by research that makes use of the Efficient Market Hypothesis (EMH). When it comes to the Efficient Market Hypothesis (EMH), there is a lot of debate going on between academics and those who handle money. According to the EMH, stock prices have the ability to accurately represent all of the relevant public information in any given situation. One of the far-reaching consequences of EMH is that the majority of people who participate in the stock market assume that the price difference between the "Buy" and "Sell" buttons will result in profits. When it comes to making financial and quantitative decisions, if stock prices completely represent all of the facts and the stock markets are efficient, then using price differential theory to buy and sell stocks would be more of a practical risk than a skill in terms of financial and quantitative decision making.[18] When dealing with a market that is very competitive, it is not reasonable to believe that any amount of study or analysis would be able to offer a benchmark that is adequate (such as the BSE Sensex). "A market is considered to be "efficient" when all of its players have access to information that is both relevant and up to date, and when a large number of rational profit maximizers are actively competing with one another to estimate the future market values of particular assets. In the case that there are a great number of competent individuals competing in a market that is operating efficiently, there will soon be no more competition there. The number of participants in the market and the rate at which information is disseminated are directly related to the efficiency of the market. As a result of the fact that financial markets are extremely efficient and asset prices reflect all publicly available financial information, the EMH hypothesis states that informed investment decisions are not capable of producing excessive returns. The EMH hypothesis states that market participants always behave in a rational manner, and arbitrageurs would promptly remedy any conduct that may be considered unreasonable. Since stock prices are always representative of their fair market value, the core premise of the theory is that it is very difficult, if not impossible, to earn a profit by acquiring undervalued stocks at a discount or by selling overpriced shares at a premium. This is because stock prices always reflect the fair market value of the stock. When it comes to outperforming the market as a whole, professional stock research and market timing strategies that are performed well have very little chance of succeeding.. The EMH theory consists of three hypotheses :

- Weak form EMH - This hypothesis test is based only on past historical information and suggests that the current stock prices already discount the past stock data, therefore Technical analysis cannot yield superior market returns. It leaves the possibility that superior fundamental analysis can yield better results and outperform the overall market.
- Semi Strong form EMH – This hypothesis asserts that both historical and current public data of the stock cannot be used to yield superior market returns. It states that as soon as the stock financial results are announced, the prices adjust quickly and discount this information. The summary of this hypothesis is that both Technical and Fundamental stock analysis cannot beat the market returns in long term. This form of EMH leaves scope for private information about the stock.
- Strong form EMH – This form of hypothesis states that all the historical, public and private data is discounted in the stock prices and there is no scope to predict stock prices and beat the collective market return. The degree to which the process may be anticipated is determined by it [9].

You can't build a decision tree without a root node, branches, and leaf nodes. Branches and leaves make up the rest of the nodes, with the root node at the very top of the tree being the only exception. To guarantee that the decision rule or test is followed, the internal node makes use of one or more data characteristics. You may define the output using the branch node. Decision trees are among the most used methods for categorization. This is because it's possible to train them without understanding how the data is distributed. It also works well with data that is both noisy and difficult to understand.

### A. AI/ML based Stock Price Models

In this work, the researcher presents the first subsystem of the DSS namely the AI/ML based stock prediction models. As a first step we evaluate the financial variables or the data set that shall be used for building the various machine learning models, These models are subjected to historical data financial data and their performance is evaluated in terms of accuracy and sensitivity of these models. As a last step various models are compared and the best performing model in terms of accuracy, reliability and sensitivity is selected to be integrated in to the overall DSS.

Financial Data Collection Methodology – In this phase, the main focus is on the data sources for the identified financial variables during the variable selection phase. The AI/ML models require large amounts of historical data for training and building the model, therefore the data sources shall include both historical data and the realtime data. The data sources must be online and openly available for efficient and error free data collection. In this phase, the researcher develops a software tool known as “Web Crawlers” for automatic collection of the data and thus reduces the manual effort in gathering this data with far less manual errors. The website which provides open source financial data about stock / companies are analyzed for their formats and the web crawlers are adjusted to collect this data automatically. Once the data is collected it needs to be checked for correctness and then it needs to be formatted in a manner that it forms the input for the various AI/ML models. Selecting ML During this phase, a number of different supervised learning AI/ML algorithms are taken into consideration for the purpose of constructing stock prediction models of various kinds. The regression (Numerical Prediction) skills of the models are measured, and the algorithms are evaluated to see whether or not they are suitable for use with financial data. On the basis of the aforementioned criteria, the AI/ML algorithms are evaluated, and a selection of them is made for the subsequent phase of model construction and training. Constructing and Training Artificial Intelligence and Machine Learning Models — The first activity that has to be completed during this phase is to choose an AI/ML model construction tool, which is also referred to as AI/ML Workbench Software. This tool is intended to be used for the purpose of training and validating the stock prediction models. After being cleaned up, the dataset from the previous step is then split into two sets: the Training set and the Validation set. The model is developed by making use of the financial variables, AI/ML techniques, and output variables that are included in the training data set. Following the construction of the model, it is trained on the historical data by making use of the training dataset. The "Trained" model is then stored in preparation for the subsequent step of model validation. The process of developing stock prediction models is repeated for each of the AI/ML algorithms that have been in the running for attention. Validation of Artificial Intelligence and Machine Learning Models Once the different "Trained" stock prediction models are ready, these models are validated by utilizing a separate validation dataset. A number of different models are executed with the help of the AI/ML model building tool, and the results of the predictions are recorded for further examination. Model performance indicators, such as accuracy levels, error rates, and other metrics, are computed and recorded for all of the AI/ML models that have been shortlisted. These values are derived from the model outputs.

The development of artificial intelligence has been a game-changer across many different industries, causing changes in the way businesses operate as well as the goods and services they provide to customers. Aamodt and Plaza (1994) assert that the use of artificial intelligence has had a significant role in the development of the stock trading industry. With the help of artificial intelligence, traders are now able to make more educated decisions and improve their trading strategies, which ultimately results in more profits and fewer risks. This article will examine the role that artificial intelligence plays in stock trading, as well as the benefits, drawbacks, and possible future repercussions of this technology. The dramatic growth in popularity of stock trading algorithms driven by artificial intelligence may be attributed, in part, to factors such as the increasing availability of enormous amounts of data and the advancements in processing power. The mounds of financial data that these computers sort through using machine learning techniques include, but are not limited to, stock price histories, business financial statements, news items, sentiment on social media, and macroeconomic indicators. These are just a few examples. The ability of artificial intelligence systems to recognize patterns and correlations allows them to outperform more traditional methods of predicting stock prices and market trends. The use of artificial intelligence in stock trading has a number of advantages, one of which is the ability to efficiently and quickly manage enormous amounts of data. As a result of their incapacity to comprehend the vast volumes of real-time information, human traders often fail to recognize opportunities or create opinions based on insufficient information. It is possible that traders may reap the benefits of the enhanced speed and accuracy of AI algorithms when it comes to processing vast volumes of data. This would allow them to make more informed trading decisions in real time. Artificial intelligence systems are able to do simultaneous evaluations of several aspects and recognize nuanced patterns that human traders could overlook. This is the cherry on top. Trading systems that are powered by artificial intelligence have a particular edge when it comes to predicting market movements and placing profitable bets because of their ability to detect patterns that have been hidden from scrutiny. As an example, artificial intelligence algorithms may discover links between stock prices and a variety of economic factors, including interest rates, inflation, and consumer sentiment, amongst others. Algorithms that are powered by artificial intelligence have the ability to adjust to changing market conditions and provide more accurate predictions when they take a more comprehensive perspective on the issue. In addition, the use of artificial intelligence for stock trading comes with the additional advantage of being able to learn and improve over time. There is a possibility that algorithms that have been taught via machine learning may learn from their errors and improve their trading strategies in reaction to new data. Trading systems that are powered by artificial intelligence have the ability to learn from their previous errors and enhance their performance in response to shifting market circumstances thanks to this capability.

While there are many advantages to using AI in stock trading, there are also some obstacles. Overfitting is a major concern because it happens when algorithms grow too good at predicting previous data and fail miserably when presented with fresh, unknown data. False signals and erroneous forecasts may emerge from overfitting, which might cause traders to lose money. The fact that AI algorithms are not easily interpretable is another obstacle. Intuition and human judgment play a role in traditional trading approaches, which help traders comprehend and justify their judgments. Contrarily, the logic behind the forecasts made by AI algorithms isn't always obvious to traders because of how complicated and opaque they might be. With the increasing use of AI in stock trading, it is crucial for both regulators and traders to establish systems that guarantee AI algorithms' decision-making process is transparent and accountable. In the future, artificial intelligence will most certainly be much more important in the stock trading industry. Recent developments in artificial intelligence have opened up exciting new avenues for the analysis of unstructured data sources, including news articles, social media feeds, and transcripts of earnings calls. Artificial intelligence algorithms may now glean sentiment, sentiment, and other useful data from various sources, giving traders a fuller picture of the market and letting them make better judgments.

### *B. Use of AI in technical analysis*

Applying AI and ML becomes a piece of cake when it comes to technical analysis, which focuses on stock volume and price movement. By examining the pattern, AI is able to create an algorithm that accurately predicts the movement of the stock index. Several forms of data are taken into account and securely ensures a sufficient return on investment by handling the data in a certain manner. Short-term and long-term investing objectives may be met with the help of AI. The amount of volatility may be reduced with the use of AI, which mostly focuses on data mining and makes decisions by reviewing past algorithms and records. Decisions made in the long run may benefit from the clear and understandable outcomes produced by AI and ML.

Traders' ability to examine and understand market data in order to make investment choices has been revolutionized by the practical uses of artificial intelligence (AI) in technical analysis. Technical analysts may sift through mountains of market data, both historical and current, in search of trends, patterns, and trading opportunities by using artificial intelligence algorithms and machine learning approaches. Better accuracy, better forecasting, and more effective trading methods are the outcomes of this. Pattern recognition is one area where artificial intelligence has proven useful in technical analysis. In order to predict how the market will behave in the future, AI systems can sift through mountains of price history data, including charts and candlestick patterns, and find patterns that repeat. Head and shoulders, double tops, and triangular formations are some examples of such patterns. Artificial intelligence programs may identify these trends and then indicate to traders whether to buy or sell, enabling them to make educated choices based on past performance. Automated trend detection is another use of AI in technical analysis. Artificial intelligence models may examine pricing data to determine the intensity and direction of market trends by using machine learning techniques. Because of this, traders can see when the market is trending upwards or downwards and profit from such shifts. Traders may increase their profits by intelligently entering or exiting positions by tracking trends. As an added bonus, technical analysts may use AI to make predictions and projections. Artificial intelligence algorithms may learn to recognize patterns and correlations in data by training them on price history and other pertinent market indicators. Traders may benefit from the AI models' ability to forecast price fluctuations, which in turn helps them to better anticipate market trends and make informed trading choices. These forecasts have the potential to shed light on important issues and aid traders in developing successful trading plans. Artificial intelligence (AI) has also been useful in improving trading tactics. Included in this category are approaches like stochastics, relative strength indicators, and moving average crossovers. Trading systems may be made more profitable and efficient with the use of AI models that adjust these tactics according to past data and current market circumstances). It should be mentioned that there are several difficulties associated with using AI in technical analysis. Overfitting is a problem that may arise when an AI model is too optimized for past data and fails to generalize well to new market circumstances. To lessen the impact of this risk, it is essential to consistently test AI models on data that isn't part of the sample and to use validating approaches that guarantee the models are reliable and resilient. By giving traders access to strong tools for evaluating and interpreting market data, the practical application of AI in technical analysis has changed the industry. When it comes to optimizing trading strategies, recognizing patterns, identifying trends, and making forecasts, AI algorithms really shine. Technical analysts may improve their performance, find more lucrative possibilities, and make more accurate forecasts by using AI. In order to keep AI models reliable and reduce the danger of overfitting, it is crucial to monitor and evaluate them. As AI continues to grow, its practical applications in technical analysis will also evolve, giving traders better decision-making tools.. So, basically, Moodle is copyrighted, but there are more liberties one may enjoy. For instance. Copying, using, and modifying Moodle is permissible so long as you adhere to the following guidelines: provide credit where credit is due; preserve the original licence and copyrights; and licence any derivative work under this licence. The open source movement is capturing the interest of educators worldwide after making a big splash in the corporate sphere. When it comes to educational use of open source apps, distance learning is at the vanguard. Open source online learning environments have recently made strides in reaction to issues with commercial systems like as WebCT and Blackboard. A limitation is the inflexibility in creating and incorporating personalised learning modules. When making a commercial product, you may only add features that the program's developers thought were essential at the time. In an open source learning environment, any learning module found on any website for open source software may be downloaded and used. The user may then tailor the app to their exact specifications by selecting from a wide range of features and components, such as homepage themes, modifying feature layouts, and choices for email, discussion forums, chat, online quizzes, and more. Also, the actual code may be changed and altered to suit individual requirements, as suggested by the open source definition. Therefore, in the event that the user chooses an open source module.

## CONCLUSION

With the help of a sound investment plan, artificial intelligence and machine learning may be used to their full potential. Consequently, when the goal is not easily defined or expressed, human intervention is necessary to correct the combination of decision variables to take emotional and non-systematic factors into consideration. With the assumption that every single company and customer starts using If machines can predict how stock values will go up and down and make sound investment decisions, we may expect a fully automated stock market and an automated return on investment. We need to change our outlook and increase our knowledge base to stay ahead in the machine-driven economy. A promising future is ahead for artificial intelligence applications in the business sector. The use of AI has the potential to completely alter the way businesses operate and create value in many domains, including decision-making, customer experience, analytics, and automation. With the further development of AI, businesses will be able to streamline their operations, make data-driven decisions, personalize customer experiences, and discover valuable insights. Nevertheless, businesses must consider the social and ethical effects of AI before implementing any policies. Businesses may seize future opportunities for innovation, growth, and competitive advantage by responsibly embracing AI and implementing proper governance. Because of this, they will be able to use AI to its maximum capacity.

## REFERENCES

1. Chowdhury, E.K. (2023). Integration of Artificial Intelligence Technology in Management Accounting Information System: An Empirical Study. In: Abedin, M.Z., Hajek, P. (eds) Novel Financial Applications of Machine Learning and Deep Learning. International Series in Operations Research & Management Science, vol 336. Springer, Cham. https://doi.org/10.1007/978-3-031-18552-6_3
2. Singh, J., & Khushi, M. (2021). Feature learning for stock price prediction shows a significant role of analyst rating. Applied System Innovation, 4(1), 1–17. https://doi.org/10.3390/asi4010017
3. Twin, A. (2021). Stock Volume of Trading. Retrieved from https://www.investopedia.com/terms/v/volumeoftrade.asp#:~:text=Volume of trade is the,and all types of commodities
4. Singh, J., & Khushi, M. (2021). Feature learning for stock price prediction shows a significant role of analyst rating. Applied System Innovation, 4(1), 1–17. https://doi.org/10.3390/asi4010017
5. Paisarn, W. (2021). Factors Influencing Retail Investors ' Trading Behaviour in the Thai Stock Market Factors Influencing Retail Investors ' Trading Behaviour in the Thai Stock Market, 15(2), 26–37. https://doi.org/10.14453/aabfj.v15i2.3
6. Thampanya, N., Wu, J., Nasir, M. A., & Liu, J. (2020). Fundamental and behavioural determinants of stock return volatility in ASEAN-5 countries. Journal of International Financial Markets, Institutions and Money, 65(March), 2020–2022. https://doi.org/10.1016/j.intfin.2020.101193
7. Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A comprehensive evaluation of ensemble learning for stock-market prediction. Journal of Big Data, 7(1). https://doi.org/10.1186/s40537-020-00299-5
8. Gupta, R., & Kapoor, N. (2020). Artificial Intelligence in Human Resource Management: New Opportunities and Challenges. Business Perspectives and Research, 8(1), 45-54
9. Suraj, E. S., Antony, J., & Nitha, K. P. (2020). Is CAPM still alive for sensex stocks in Indian stock market? - An empirical analysis. International Journal of Management, 11(4), 210–220. https://doi.org/10.34218/IJM.11.4.2020.022
10. Thampanya, N., Wu, J., Nasir, M. A., & Liu, J. (2020). Fundamental and behavioural determinants of stock return volatility in ASEAN-5 countries. Journal of International Financial Markets, Institutions and Money, 65(March), 2020–2022. https://doi.org/10.1016/j.intfin.2020.101193
11. Vijh, M., Chandola, D., Tikkiwal, V. A., & Kumar, A. (2020). Stock Closing Price Prediction using Machine Learning Techniques. Procedia Computer Science, 167(2019), 599–606. https://doi.org/10.1016/j.procs.2020.03.326
12. L. Ji, X. Zhang, L. Zhang, Research on the Algorithm of Education Data Mining Based on Big Data, in: 2020 IEEE 2nd International Conference on Computer Science and Educational Informatization (CSEI), 2020, pp. 344–350.
13. Alkubaisi, G. A. A. J. (2019). The Role of Ensemble Learning in Stock Market Classification Model Accuracy Enhancement Based on Naive Bayes Classifiers. International Journal of Statistics and Probability, 9(1), 36. https://doi.org/10.5539/ijsp.v9n1p36
14. Areiqat, A. Y., Abu-Rumman, A., Al-Alani, Y. S., & Alhorani, A. (2019). Impact of behavioral finance on stock investment decisions applied study on a sample of investors at Amman Stock Exchange. Academy of Accounting and Financial Studies Journal, 23(2), 1–17
15. Basak, S., Kar, S., Saha, S., Khaidem, L., & Dey, S. R. (2019). Predicting the direction of stock market prices using tree-based classifiers. North American Journal of Economics and Finance, 47(January), 552–567. https://doi.org/10.1016/j.najef.2018.06.013.
16. Chong, E., Han, C., & Park, F. (2017). Deep Learning Networks for Stock Market Analysis and Prediction. Expert Systems with Applications, 83(April), 187–205. https://doi.org/10.1016/j.eswa.2017.04.030

17. Dash, R., & Dash, P. K. (2016a). A hybrid stock trading framework integrating technical analysis with machine learning techniques. Journal of Finance and Data Science, 2(1), 42–57. https://doi.org/10.1016/j.jfds.2016.03.002
18. Dash, R., & Dash, P. K. (2016b). A hybrid stock trading framework integrating technical analysis with machine learning techniques. The Journal of Finance and Data Science, 2(1), 42–57. https://doi.org/10.1016/j.jfds.2016.03.002