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Investment Portfolio Management System

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Abstract: The idea of this project is to automate the process of investing or trading based on users choice , by providing references to financial markets trajectory. This project helps a retail investor to meet his financial goals by automating the process and thereby remains manageable for them. The current projects usually reside on the principle of predicting the trend of the market or particular financial instrument .This can be done by using LSTM or prophet seasonality prediction model to predict non-linear trend in the market. Designing a bot to invest in instruments based on the users requirements will further help in automating the entire process. This ideated system is thought by integrating the smart predicting feature of the machine.

I. INTRODUCTION

Investors are constantly seeking out ways to make more informed investment decisions. One popular approach is using mathematical models, known as quantitative strategies, to predict the likelihood of success. However, machine learning in investing offers a more efficient and hands-off approach for making better investment decisions. By using machine learning algorithms, investors can rely on automated processes to analyze data and make informed predictions about the success of their investments .

The idea of this project is to automate the process of investing or trading based on users choice , by providing references to financial markets trajectory. Previous successful approaches to the problem of algorithmic trading that do not rely on forecasting future prices and are fully based on machine learning have treated the problem as a Reinforcement Learning (RL) issue. These model-free, fully machine-learning methods use RL algorithms to analyze data and make decisions about trading actions. This ideated system is thought to be built by integrating the smart predicting feature of machine learning predicting trends along with bot for automating the process of investing.

II. LITERATURE SURVEY

There are many research papers and articles that have been published on the topic of investment portfolio management. Some areas of research include portfolio optimization, asset allocation, risk management, and performance evaluation. Here are a few examples of research in these areas:

1) "Portfolio Optimization: A Review" by R.A. Litterman and Y.T. Wu (1998) provides an overview of the various approaches to portfolio optimization, including Markowitz mean-variance optimization, Black-Litterman model, and heuristic algorithms.
2) "The Theory and Practice of Asset Allocation" by P.A. Samuelson and W.F. Sharpe (1994) discusses the principles of asset allocation and how to implement an effective asset allocation strategy.
3) "Risk Management: Coordinating Corporate Investment and Financing Policies" by F. Black and M. Scholes (1972) presents a framework for managing risk in a portfolio of assets, including the use of financial instruments such as futures and options.
4) "Evaluating Portfolio Performance" by B.J. Brinson, G.L. Beebower, and D.D. Peters (1986) discusses the various methods for evaluating the performance of an investment portfolio, including risk-adjusted measures such as the Sharpe ratio and the Treynor ratio.

These are just a few examples of the many research works on investment portfolio management.

III. METHODOLOGY

A. *LSTM Model*

Recurrent neural networks (RNNs) can be enhanced by using the long short term memory (LSTM) paradigm, which acts as a form of short-term memory by allowing previously determined information to be used in the current neural network. This is useful for urgent tasks that require the use of earlier data. However, it is possible that we may not have a complete list of all the earlier data for a particular neural node. LSTMs are a popular type of neural network within RNNs and are used for a variety of sequence modeling tasks across a range of application areas, including natural language processing, video, geographic information systems, and time series analysis. One of the main challenges with RNNs is the vanishing gradient problem, which occurs due to the repetitive use of the same parameters at each time step. To address this problem, various techniques can be applied at each time step.

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In these cases, we aim to find a balance by generalizing variable-length sequences while still maintaining a fixed number of learnable parameters. To do this, we introduce unique parameters at each step and use gated RNN cells such as LSTM and GRU. This allows us to effectively handle variable-length sequences while still maintaining a fixed number of learnable parameters overall.

B. Portfolio Management Challenge

The challenge that the modern youth face when it comes to the subject of finance is based on how they manage their portfolio while striving for financial independence. Strategy is an important
aspect for meeting criteria of successful portfolio. Hence,Taking into consideration a diverse portfolio paired with the ever-changing dynamics of the market presents a new challenge: determining an investment strategy to match your company's goals. Not every investment strategy is the same. Some investors and companies may be seeking a high-risk portfolio, bringing them the highest return available in the market.
Others may be long term investors, strategizing for the future.Financial challenges also go beyond the numbers to evaluating the structure and workflow of the personnel and management. Inefficiency and ineffective strategies being deployed can be the cause of financial loss to a portfolio, just as severely as investing in an equity projected to be bearish. Wasted money needs to be identified and new tactics must be developed for growth.There is a large proportion of beginners entering the arena of investment , most of whom don't have enough knowledge or market exposure . This could lead to an increased number of failures when it comes to the percentage of the population profiting from investment.

C. Background

In recent years, there has been increasing interest in using machine learning algorithms to automate investment portfolio management. Machine learning algorithms are designed to learn from data and improve their performance over time, which makes them well-suited for tasks such as analyzing financial data and making investment decisions.
There are several ways in which machine learning can be applied to portfolio management. For example, machine learning algorithms can be used to analyze financial data and identify patterns or trends that may be useful for making investment decisions. They can also be used to build models that can predict the performance of different investments or predict market movements.
There are several potential benefits to using machine learning for portfolio management. For example, machine learning algorithms can process large amounts of data quickly and accurately, which can help investment professionals to identify trends and patterns that might be difficult to detect manually.
Additionally, machine learning algorithms can be trained to make decisions based on multiple factors, which can help to improve the diversification of a portfolio and reduce risk.
Overall, the use of machine learning in portfolio management is an active area of research and development, and it is likely that we will see continued growth and innovation in this area in the coming years.

D. Machine Learning Techniques

Machine learning is a term that has been in focus for many decades now. Machine learning facilitates traders more than traditional algorithmic trading The field of machine learning is receiving a lot of attention due to the current interest in artificial intelligence and its various applications.
Machine learning techniques can be broadly classified into three categories based on the type of data they use and whether they require input from an external agent: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves the use of labeled data to make predictions or decisions, unsupervised learning involves the use of unlabeled data to identify patterns or groupings within the data, and reinforcement learning involves the use of an external agent to take actions within an environment in order to maximize a reward or objective Before diving into the machine learning preferred as such ,it's important to know about how such algorithms help in predicting.
Further details about how data for training is given in the upcoming section. Machine learning applies a process to detect the hidden patterns in dataset from various data sources. Earlier machines were designed to solve specific problems by following a set of instructions programmed by humans. In contrast, modern machine learning systems use algorithms that allow the machine to learn from data and make decisions on its own. This means that machine learning systems are able to adapt and improve their performance over time, without the need for explicit human guidance.

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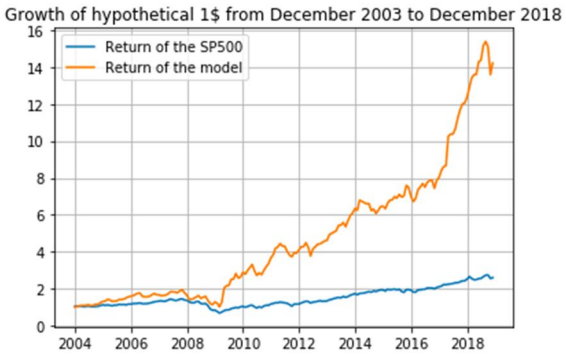


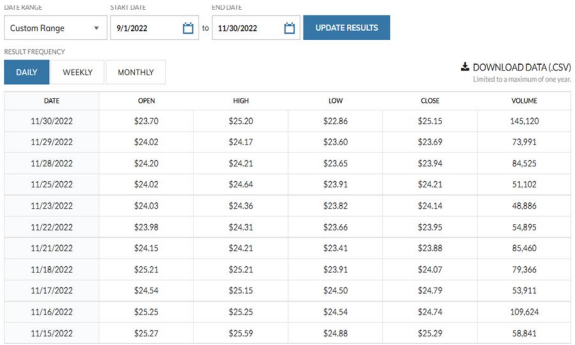
E. Dataset

Market data contains a range of data such as price, open, high, low, close, volume etc. Market data refers to the information and statistics that are generated by financial markets, including stock prices, indices, exchange rates, and commodity prices. This data is available for a wide range of global markets, covering various asset classes such as stocks, indices, forex, and commodities.

Market data is used by traders to assess the worth of assets of various companies, and will give them an idea about when to buy or sell stocks. The Aim of using market data is to get as much information about the asset the trader is planning on buying.

Market data is generated in real time,which can be used to make quick but informed decisions. Market

Data can be also used to access historical prices ,these prices are a crucial part of technical analysis, and can be used when creating a strategy for future .



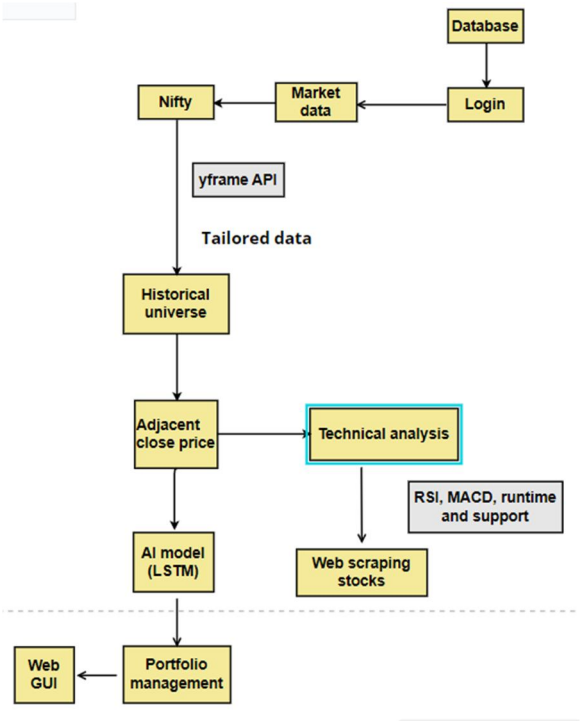
DATE	OPEN	HIGH	LOW	CLOSE	VOLUME
11/30/2022	$23.70	$25.20	$22.86	$25.15	145,120
11/29/2022	$24.02	$24.17	$23.60	$23.69	73,991
11/28/2022	$24.20	$24.21	$23.65	$23.94	84,525
11/25/2022	$24.02	$24.64	$23.91	$24.21	51,102
11/23/2022	$24.03	$24.36	$23.82	$24.14	48,886
11/22/2022	$23.98	$24.31	$23.66	$23.95	54,895
11/21/2022	$24.15	$24.21	$23.41	$23.88	85,460
11/18/2022	$25.21	$25.21	$23.91	$24.07	79,366
11/17/2022	$24.54	$25.15	$24.50	$24.79	53,911
11/16/2022	$25.25	$25.25	$24.54	$24.74	109,624
11/15/2022	$25.27	$25.59	$24.88	$25.29	58,841

F. Technical Indicators

1) *Oscillators:* Technical indicators that oscillate between a local minimum and maximum, such as the stochastic oscillator, MACD, or RSI, are typically plotted above or below a price chart rather than being overlaid directly on it. In this article, we will primarily be focusing on this type of technical indicator.
2) *MACD:* The MACD indicator is a tool used by traders to assess the direction and strength of a trend. When the MACD is above zero, it indicates that the price is in an uptrend. When the MACD is below zero, it indicates that the price is in a downtrend. The MACD also generates signals that can be used to make trading decisions
3) *Relative Strength Index:* The relative strength index (RSI) is a technical indicator that is used to measure the strength of a trend. It oscillates between zero and 100, with higher values indicating that recent price gains are stronger than recent price losses. The RSI is often used to identify overbought and oversold conditions in the market. If the RSI moves above 70, it is considered overbought and the asset may be due for a correction. If the RSI falls below 30, it is considered oversold and the asset may be due for a rally. In addition to these uses, the RSI can also be used to identify momentum and trend strength.
4) *On-Balance Volume:* The on-balance volume (OBV) indicator is used to measure the flow of volume in a security over time. It is calculated by adding up volume (the volume of trades on days when the price goes up) and subtracting down volume (the volume of trades on days when the price goes down). If the OBV is rising, it means that buyers are outpacing sellers and pushing the price higher. If the OBV is falling, it means that selling volume is outpacing buying volume, which could lead to lower prices. The OBV can be used to confirm trends: if the price and OBV are both rising, it can indicate that the trend is continuing.

5) *Accumulation/Distribution Line:* The accumulation/distribution line (A/D line) is a technical indicator that is used to measure the flow of money into and out of a security. It is similar to the on-balance volume (OBV) indicator, but takes into account the trading range for the period as well as the closing price. If the stock closes near its high, the A/D line gives more weight to the volume traded. If the stock closes near the middle of its trading range, the volume is given less weight. The A/D line can be used to confirm trends, similar to the OBV. In some cases, the OBV may be a more reliable indicator, while in others the A/D line may be more effective.
6) *Average Directional Index:* The average directional index (ADX) is a technical indicator that is used to measure the strength and momentum of a trend. It is typically plotted on a chart as a single line, with values ranging from 0 to 100. When the ADX is above 40, it indicates that the trend has a strong directional strength, whether up or down. When the ADX is below 20, the trend is considered weak or non-trending. The ADX is usually accompanied by two additional lines, known as DI+ and DI-. These lines, which are often colored red and green, respectively, are used to show the direction of the trend and the momentum of the trend. All three lines work together to provide a comprehensive view of the trend.

IV. IMPLEMENTATION



The system is then configured to meet specific needs, including setting up user accounts, defining asset classes, and establishing risk management parameters. Data integration is crucial, ensuring accurate and reliable information from various sources. If transitioning from an existing system, data migration is performed. Thorough testing and quality assurance are conducted to identify and resolve any issues. User training is provided to ensure effective utilization of the system. Once tested and trained, the system is deployed in a production environment, with ongoing maintenance and support to address any issues and stay updated with upgrades and security patches.

V. TOOLS AND SOFTWARE

1) *Git (Version 2.31.1):* It is for version control introduce new features, enhancements, bug fixes, or security updates. It's important to use a specific version to ensure compatibility with other tools and services used in the development process.
2) *Github:* For hosting the project repository and enabling collaboration. It provides a robust platform for hosting the project repository and facilitating collaboration among developers. It streamlines the development process, promotes code quality, and enables effective project management for the portfolio management system.

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VI. RESULT & ACCURACY

The system utilizes technical analysis, which involves analyzing historical price patterns and market trends to identify potential entry and exit points for investments. It also employs machine learning forecasting using Long Short-Term Memory (LSTM) models to predict future stock prices based on historical data and patterns. To gather relevant information about trending stocks, the system includes web scraping modules.

These modules retrieve data from online sources such as news articles, financial reports, and social media sentiment analysis, providing valuable insights for investment decisions. However, it is emphasized that investing in the stock market carries inherent risks. Therefore, the system should incorporate robust risk management strategies.

This may involve diversifying the portfolio, setting risk limits, regularly monitoring investments, and implementing stop-loss measures. Since the system is in the beta state, ongoing testing, evaluation, and refinement are necessary to improve its performance, accuracy, and overall effectiveness. Continuous updates are important to address any limitations or areas for enhancement that are identified during testing. We give some of the outcomes from using the algorithm on stocks traded on the Australian Stock Exchange in this section. The adaptive network is tested using two alternative setups. The first maintains a portfolio using a variable rulebase, and the second utilizes a fixed rulebase that does not adjust to changing market conditions. The weighted return on investment fitness objective is used by both.

Stocks traded on the Australian Stock Exchange are used to create portfolios using the system discussed in the previous sections.

Exchange (hereinafter ASX) (hereafter ASX). From August 2001 to December 2006, two distinct portfolios are created each month. The first one, known as the "Adaptive EA" portfolio, is made via a full adaptive evolutionary process.

A rule base is constructed for the first window and used for the remainder of the simulation to create the second one using a static rule base (see II-F). This portfolio, referred to as the "Static EA," serves as a benchmark for comparison when evaluating the benefits of utilizing an adaptive rule base.

VII. IMPLICATION AND MITIGATION STRATEGIES

A. *Data Security*

1) *Implication:* Mishandling or unauthorized access to sensitive client and financial data can lead to financial loss, reputational damage, and legal consequences.
2) *Mitigation:* Implement robust data security measures such as encryption, access controls, secure network infrastructure, regular data backups, and strict adherence to regulatory compliance standards.

B. *System Reliability and Availability*

1) *Implication:* Downtime or system failures can disrupt portfolio management operations, result in missed investment opportunities, and impact client satisfaction.
2) *Mitigation:* Employ redundant systems, disaster recovery plans, and proactive monitoring to ensure high system availability. Conduct regular maintenance, testing, and performance optimizations to minimize system downtime.

C. *Client Communication and Transparency*

1) *Implication:* Insufficient communication, poor transparency, and lack of timely updates can result in client dissatisfaction and loss of trust.
2) *Mitigation:* Establish clear and effective communication channels, provide regular portfolio updates, performance reports, and investment insights. Foster transparency in investment strategies, risks, and fees, ensuring clients have access to relevant information and a clear understanding of their portfolio.

D. *Operational Efficiency*

1) *Implication:* Inefficient processes, manual workflows, and lack of automation can hinder the effectiveness and scalability of portfolio management operations
2) *Mitigation:* Implement advanced portfolio management software, automation tools, and integrated systems to streamline processes, enhance efficiency, and reduce errors. Embrace technological advancements such as AI, machine learning, and natural language processing to optimize investment decision-making and reporting.

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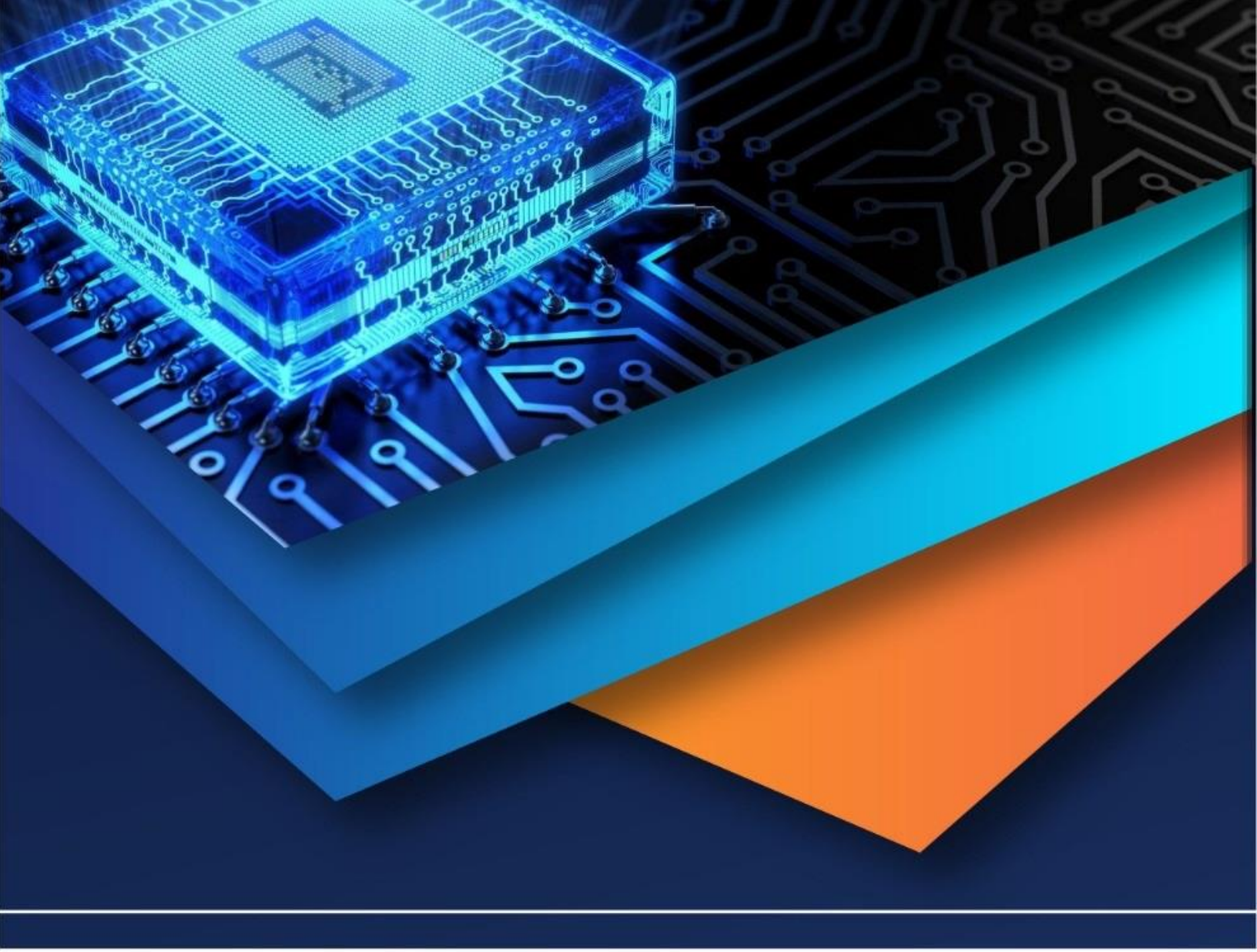
VIII. CONCLUSION AND FUTURE RESEARCH

This study focuses on machine learning-based investment strategies that automate the process of trading or investing depending on user preferences by using historical data on financial markets.

The work's success demonstrates unequivocally that machine learning techniques may be utilized to create varied portfolios that outperform the marketplace indices. Therefore with the help of machine learning we can guide the broker api to invest in security assets based on his/her relevant ROI he set up. This idea is believed to help millennial investors to help achieve financial freedom and earn part time income from this source. In this project we plan to utilize a single machine learning algorithm , this could lead to just adequate performance ,so it would be good enough by adding more than two algorithms and optimizing the result to lead to even better performance of the systems prediction

REFERENCES

[1] Dhansay, I., & Pillay, K. An Intelligent System for Automated Portfolio Management using Graph Neural Networks and Semantic Bayesian Networks.
[2] F. Gu, Z. Jiang and J. Su, "Application of Features and Neural Network to Enhance the Performance of Deep Reinforcement Learning in Portfolio Management," 2021 IEEE 6th International Conference on Big Data Analytics (ICBDA), 2021, pp. 92-97, doi: 10.1109/ICBDA51983.2021.9403044.
[3] O. Rossoshanskaya, O. Biryukov, "APPROACH TO THE CALCULATION OF CONSOLIDATED RATINGS FOR THE TASKS OF MANAGING HIGHER EDUCATION INSTITUTIONS", Intelligent computer-integrated information technology in project and program management, pp.281, 2020.
[4] S. Bushuyev, N. Gaydukova, N. Bushuyeva and I.Achkasov,"Evaluation of the investment projects portfolio efficiency," 2021 IEEE 16th International Conference on Computer Sciences and Information Technologies (CSIT), 2021, pp. 351-354, doi: 10.1109/CSIT52700.2021.9648798.
[5] Y. S. Asawa, "Modern Machine Learning Solutions for Portfolio Selection," in IEEE Engineering Management Review, vol. 50, no. 1, pp. 94-112, 1 First Quarter,march 2022, doi: 10.1109/EMR.2021.3131158.
[6] J. West, "Inferring Risk Aversion for Decentralized Investment Portfolios," 2015 IEEE First International Conference on Big Data Computing Service and Applications, 2015, pp. 341-346, doi: 10.1109/BigDataService.2015.50.
[7] Fachrudin, K. A., & Fachrudin, H. T. (2015). The study of investment portfolio management and sustainability of property and real estate companies in the Indonesia stock exchange. Procedia-Social and Behavioral Sciences, 211, 177-183
[8] E. Tyukhova and D. Sizykh, "The Cluster Analysis Method as an Instrument for Selection of Securities in the Construction of an Investment Portfolio," 2019 Twelfth International Conference "Management of large-scale system development" (MLSD), 2019, pp. 1-3, doi: 10.1109/MLSD.2019.8910991.
[9] D. Sizykh, "Performance Indicators Comparative Analysis of Stocks Investment Portfolios with Various Approaches to Their Formation," 2020 13th International Conference "Management of large-scale system development" (MLSD), 2020, pp. 1-5, doi: 10.1109/MLSD49919.2020.9247833.
[10] B. Li, "Research on Optimal Portfolio of Financial Investment Based on Genetic Algorithm," 2019 International Conference on Economic Management and Model Engineering (ICEMME), 2019, pp. 497-500, doi: 10.1109/ICEMME49371.2019.00104.
[11] A. Syrovatkin, "Mixed Investment Portfolio with Limited Asset Selection," 2020 13th International Conference "Management of large-scale system development" (MLSD), 2020, pp. 1-5, doi: 10.1109/MLSD49919.2020.9247765.
[12] S. Bushuyev, N. Gaydukova, N. Bushuyeva and I. Achkasov, "Evaluation of the investment projects portfolio efficiency," 2021 IEEE 16th International Conference on Computer Sciences and Information Technologies (CSIT), 2021, pp. 351-354, doi: 10.1109/CSIT52700.2021.9648798.
[13] Trippi, R. R. (1989). A decision support system for real estate investment portfolio management. Information & Management, 16(1), 47-54.
[14] Dzikevičius, A., & Vetrov, J. (2013). Investment portfolio management using the business cycle approach. Business: Theory and Practice, 14(1), 57-63.



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