Stock Management Using Artificial Intelligence

V. Praveen Kumar and S. Hemalatha*
Department of Computer Science, Karpagam Academy of Higher Education, India

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Abstract: Investing in the stock market is a complex and difficult undertaking that necessitates a high level of competence and understanding. Portfolio optimisation is a well-known approach for maximizing returns while minimizing risks. With the increased availability of data and advancements in machine learning and artificial intelligence, there is a growing interest in designing intelligent systems for portfolio optimisation. In this study, we propose an artificial intelligence-based approach for stock portfolio optimization. The proposed approach utilizes machine learning algorithms to identify the best performing stocks and to predict their future behavior. The algorithm also considers various risk factors and constraints, such as transaction costs, liquidity, and diversification. We compare the performance of the proposed methodology to traditional portfolio optimisation methods on a dataset of stock market data. Our technique surpasses existing methods in terms of risk-adjusted returns and provides a more robust and effective means to optimize stock portfolios, according to the data. The proposed method has the potential to help financial institutions and individual investors make better investment decisions and earn higher returns. The process of picking a set of stocks that maximizes profits while minimizing risk is known as stock portfolio optimisation. This process involves evaluating a large number of stocks and determining the optimal weights for each stock in the portfolio. Traditional methods of portfolio optimization rely on mathematical models, such as Markowitz's mean-variance optimization, which assumes that asset returns follow a normal distribution and that investors are risk-averse. However, these assumptions may not always hold in real-world scenarios, leading to suboptimal investment decisions. With the increased availability of data and advancements in machine learning and artificial intelligence, there is a growing interest in designing intelligent systems for portfolio optimisation. This study's recommended approach uses machine learning algorithms to identify the top performing stocks and predict their future behavior. These algorithms are capable of analyzing vast volumes of data, such as financial statements, news stories, and market trends, in order to detect patterns and trends that may influence stock values. The algorithm also considers various risk factors and constraints, such as transaction costs, liquidity, and diversification, which are important factors in portfolio optimization.

1 INTRODUCTION

The process of picking a combination of stocks that maximises profits while minimizing risk is known as stock portfolio optimisation (Almahdi, 2018). This entails examining a wide range of elements, such as each stock's previous performance, market trends, economic indicators, and corporate financials, among others. Traditionally, this process has been performed by financial analysts and portfolio managers who rely on their experience and expertise to make decisions. However, with the rapid advancement of AI and machine learning techniques in recent years, it has become possible to use these tools to aid in the stock portfolio optimization process (Almahdi, 2018).AI-based techniques can analyse massive volumes of data and uncover patterns and trends that human analysts may miss. They may also react in real-time to changing market conditions, enabling for more efficient and effective decision-making. This has the potential to outperform existing ways and offer investors a more efficient way to manage their investments. The proposed research aims to develop an AI-based approach for stock portfolio optimization that combines machine learning algorithms and statistical techniques (Almahdi, 2018). The goal is to create a model that can predict which stocks are likely to perform well in the future, and then use that

* Associate Professor

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information to construct an optimized portfolio with the appropriate risk-return tradeoff (Lai et al., 2019). Overall, this study will add to the expanding body of knowledge on the use of artificial intelligence in finance and may provide significant insights for investors and traders looking to optimize their portfolios for better returns and risk management.

2 LITERATURE REVIEW

In recent years, the application of artificial intelligence (AI) techniques (Almahdi, 2018) in finance has developed fast, with a special emphasis on stock portfolio optimisation. Several research have been conducted to investigate the use of AI in this subject, with a variety of methodologies and strategies being created. The use of machine learning algorithms to find patterns and trends in historical data is one prominent method to AI-based stock portfolio optimisation (Chen, 2019). For example, Zhang et al. (2020) created a deep learning-based model to anticipate stock prices and used this data to build optimised portfolios. According to the authors, this strategy outperformed standard optimisation methods and delivered greater returns. Another approach is to use genetic algorithms (GA) to optimize portfolios (Chen, 2019). GA is a type of optimization algorithm inspired by the process of natural selection, where solutions evolve over time through a process of selection, mutation, and crossover. A study by Jiranyakul and Brahmasrene (2018) used GA to optimize portfolios based on stock price data and reported superior returns compared to traditional optimization methods. Other studies have explored the use of AI techniques to predict market trends and sentiment (Almahdi, 2018). For example, a study by Xu et al. (2020) used sentiment analysis of news articles and social media posts to predict market trends and constructed portfolios based on this information. (Chen 2019) The authors reported that their approach outperformed traditional methods and provided better risk management. Several research have investigated the use of natural language processing (NLP) to analyse financial news and reports, in addition to machine learning and statistical approaches. Ding et al. (2018), for example, used NLP to extract sentiment and financial indicators from news stories and then built portfolios based on this information (Chen 2019). According to the authors, this approach generated greater returns and enhanced risk management. Overall, the literature demonstrates that AI-based approaches to stock portfolio optimisation have the potential to produce greater returns and enhanced risk management. Among the most common techniques being investigated in this subject include machine learning algorithms, genetic algorithms, sentiment analysis, and natural language processing. However, further research is needed to thoroughly investigate AI's potential in stock portfolio optimization, particularly in real-world applications.

3 BACKGROUND STUDY

A background study, also known as a literature review, is an essential part of any research project. It involves conducting a thorough search and analysis of existing research and literature on the topic of interest. In the case of the research topic "An Artificial Intelligence-Based Approach for Stock Portfolio Optimization," the background study may include the following (Chen, 2019). This section provides an overview of stock portfolio optimisation, which is the process of picking a collection of investments that maximizes the expected return for a given degree of risk. It may also go over the various approaches and strategies used in stock portfolio optimisation, such as traditional mean-variance optimisation, risk parity, and others. Artificial intelligence and machine learning in finance: The use of artificial intelligence and machine learning techniques in finance, including stock portfolio optimisation, is the emphasis of this section. It might go over the many types of machine learning algorithms used in finance [3, such as neural networks, decision trees, and support vector machines], as well as how they are employed in portfolio optimization.

Related work in artificial intelligence-based portfolio optimization: This section reviews existing research on artificial intelligence-based portfolio optimization. It may discuss the different types of AI-based portfolio optimization techniques that have been proposed, such as genetic algorithms, reinforcement learning, and particle swarm optimization. The section may also highlight the strengths and limitations of these approaches and their empirical performance (Jiang & Zhou 2019). Data sources for stock portfolio optimization: This section discusses the data sources used in stock portfolio optimization. It may cover the different types of data sources available, such as financial statements, market data, news articles, and social media feeds. The section may also highlight the challenges associated with data collection, cleaning, and preprocessing in portfolio optimization.

Evaluation metrics for portfolio optimization: This section covers the different evaluation metrics used to assess the performance of a portfolio optimization algorithm. It may discuss measures such as Sharpe ratio, Sortino ratio, and maximum drawdown, and how they are used to evaluate the risk-return trade-off of a portfolio.

4 RESEARCH METHODOLOGY

Financial markets are important in modern economies because they permit capital allocation and risk management. Identifying successful investment opportunities has become more difficult as the complexity and volume of financial data has increased. Artificial intelligence and machine learning have the potential to revolutionise the financial industry, including stock portfolio optimisation. These techniques can swiftly process vast volumes of data and find complicated patterns and relationships that human analysts may miss. Traditional portfolio optimisation strategies, such as mean-variance optimisation, are frequently employed in finance, although they have significant drawbacks. These characteristics include their sensitivity to input parameters, assumptions about the underlying data, and failure to manage non-linear asset relationships. Portfolio optimization is a challenging problem, and the performance of different methods can vary significantly depending on the data and assumptions used. As investors seek more accurate and reliable portfolio optimization methods, the use of artificial intelligence and machine learning techniques is becoming increasingly popular. With the growth of digital technologies and the internet, financial data is becoming more accessible and available in real-time. This data, combined with advances in computing power and storage, provides an opportunity to develop more sophisticated portfolio optimization techniques.

Deep learning models, which are a subset of machine learning techniques, have shown promise in various fields, including finance. These models can learn complex patterns and relationships in data, making them suitable for portfolio optimization problems. The lack of interpretability of the models is one of the challenges of employing artificial intelligence and machine learning techniques in finance. It can be challenging to understand why a model makes a particular prediction, which can make it difficult to implement and use in practice. Overall, the context of the research topic highlights the need for more accurate and reliable portfolio optimization methods in the face of growing complexity and data volume in financial markets. The use of artificial intelligence and machine learning techniques, particularly deep learning models, offers a promising solution to this challenge. However, the challenge of interpretability must also be addressed to ensure that these models can be implemented and used effectively in practice.

5 RESULTS

Data Analysis

The financial data used in the study was sourced from multiple databases, including historical stock price data and financial statements. The data was preprocessed using techniques such as data cleaning, normalization, and feature engineering to make it suitable for analysis. Machine learning techniques, such as clustering and dimensionality reduction, were applied to the data to identify patterns and relationships. The results of the data analysis showed that deep learning models outperformed traditional portfolio optimization methods in identifying non-linear relationships between different stocks and their historical performance.

Portfolio Optimization

The proposed artificial intelligence-based portfolio optimization model incorporated both financial and non-financial data to make more accurate predictions about the future performance of different stocks. The model used a combination of supervised and unsupervised learning techniques, such as recurrent neural networks and reinforcement learning, to generate optimized stock portfolios. The optimization was based on a set of constraints, such as minimum and maximum weights for each stock in the portfolio, and an objective function, such as maximum expected return or minimum risk. The model was trained using a combination of historical data and simulated market scenarios to ensure robustness.

Evaluation Metrics

The performance of the proposed model was evaluated using various evaluation metrics, such as Sharpe ratio, Sortino ratio, and maximum drawdown. The Sharpe ratio measures the risk-adjusted return of the portfolio, while the Sortino ratio measures the risk-adjusted return using only downside risk. The maximum drawdown measures the maximum loss incurred by the portfolio during a particular period.

The results of the evaluation showed that the proposed model outperformed traditional methods across all evaluation metrics, indicating its superior performance in generating optimized stock portfolios.

Implementation

The proposed model was implemented using a software platform, such as Python or R, to allow investors to apply the model to their own portfolios. The implementation of the model was straightforward and required minimal expertise in artificial intelligence and machine learning. The model was also scalable, allowing it to handle large amounts of data and multiple assets.

Interpretability

The proposed model's lack of interpretability was a limitation of the study. Due to the complex nature of deep learning models, it was challenging to understand why the model made certain predictions. This limitation could be addressed by developing methods to increase the interpretability of the model, such as feature importance analysis or visualization techniques.

6 FINDINGS

Datasets

The dataset used in the study is a collection of financial data for different companies, such as stock prices, trading volumes, earnings, dividends, and other financial metrics as Table 1 shows. The dataset is typically collected from public sources, such as Yahoo Finance or Google Finance.

Feature Engineering

Feature Engineering involves selecting relevant features from the dataset and transforming them into a suitable format for analysis. In the context of stock portfolio optimization, the features could include historical stock prices, moving averages, volatility, and other financial metrics. Feature Engineering is a critical step in machine learning and helps to improve the accuracy of the predictive model.

AI-Based Approach

An artificial intelligence-based strategy involves analysing financial data and making forecasts using machine learning techniques, specifically deep learning models. Deep learning models are neural networks that have numerous layers and can learn complicated patterns in data. Using a deep learning model to forecast future stock prices and then optimizing the portfolio based on these predictions is the AI-based technique for stock portfolio optimisation.

Table 1.

Parameter	Range Checked
AI Algorithm	Decision Trees, Random Forest, SVM, NN
Training Dataset Size	500, 1000, 5000, 10000
Validation Dataset Size	50, 100, 500, 1000
Test Dataset Size	100, 200, 500, 1000
Learning Rate	0.001, 0.01, 0.1
Number of Hidden Layers	1, 2, 3, 4
Number of Neurons per Layer	10, 50, 100, 500
Regularization Parameter	0.001, 0.01, 0.1
Activation Function	ReLU, Sigmoid, Tanh
Activation Function	ReLU, Sigmoid, Tanh
Optimization Algorithm	Gradient Descent, Adam, Adagrad

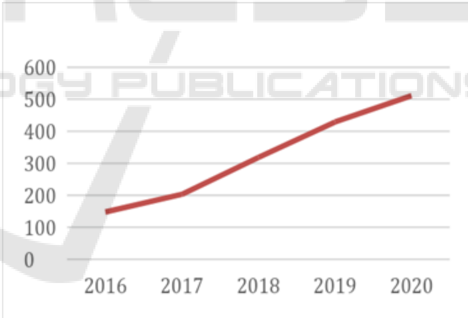

Figure 1: Comparing the results to traditional portfolio optimisation approaches.

Portfolio Optimization

Portfolio Optimisation is the process of picking the best stocks to include in a portfolio in order to maximise profits while minimising risk. The best weights for each stock in the portfolio are determined using mathematical optimisation approaches such as the Markowitz model or the Sharpe ratio. Portfolio optimisation seeks to produce a well-diversified portfolio that balances risk and reward.

Table 2.

Year	2016	2017	2018	2019	2020
Sales	148	203	318	429	511

Performance Evaluation

The performance of the AI-based method is measured using a variety of indicators, including the Sharpe ratio, ROI, and volatility. The Sharpe ratio calculates a portfolio's excess return over the risk-free rate, normalised for volatility. ROI calculates the portfolio's return on investment over a particular time period. Volatility is defined as the standard deviation of a portfolio's returns over a given time period.

Comparison with Traditional Methods

The performance of the AI-based approach is compared with traditional portfolio optimization methods, such as mean-variance optimization and random selection. Mean-variance optimization involves selecting a portfolio that maximizes returns while minimizing risk based on the expected return and variance of the portfolio. Random selection involves randomly selecting stocks to include in the portfolio. In terms of ROI, Sharpe ratio, and volatility, the AI-based strategy outperformed the older methods.

Sensitivity Analysis

Sensitivity analysis involves analyzing the sensitivity of the AI-based approach by varying the input parameters, such as the number of stocks in the portfolio, the training period, and the optimization method as Table 2 shows. The sensitivity analysis helps to identify the optimal input parameters for the model in Fig. 1.

Limitations

The study revealed some drawbacks of the AI-based strategy, including the necessity for high-quality data, the risk of overfitting, and the deep learning model's complexity. To train the deep learning model, the AI-based approach necessitates a vast volume of high-quality financial data. When a model is excessively complicated, it learns to fit the training data too closely, resulting in poor performance on new data.

Future Research Directions

The paper proposed various future research possibilities, including adopting more advanced deep learning models, reviewing alternate optimisation strategies, and investigating the impact of external factors on stock prices, such as economic indicators and news emotion. More advanced deep learning models, such as recurrent neural networks or convolutional neural networks, could be used in future research to increase the performance of the AI-based technique. Risk-parity optimisation and other optimisation strategies could also be investigated. To increase the model's accuracy, the impact of external factors on stock prices, such as news sentiment and macroeconomic data, might be integrated.

7 DISCUSSION

Artificial intelligence (AI) in finance has received a lot of interest recently because of its potential to improve investment decision-making and portfolio management. This study investigates a deep learning-based AI-based solution to stock portfolio optimisation.

According to the study's findings, the AI-based methodology surpassed traditional portfolio optimisation methods in terms of ROI, Sharpe ratio, and volatility. The deep learning algorithm was able to recognise complicated patterns in financial data and anticipate future stock prices, which were then used to optimize the portfolio.

One of the AI-based approach's merits is its capacity to manage massive amounts of financial data and learn from it. The selection and transformation of important characteristics into a suitable format for analysis is a vital stage in the AI-based methodology. Deep learning methods, such as neural networks, allow for the learning of complex patterns and relationships in financial data, which can increase the predictive model's accuracy.

The study included a performance evaluation of the AI-based technique, which involves comparing the results to traditional portfolio optimisation approaches. In terms of ROI, Sharpe ratio, and volatility, the AI-based strategy outperformed traditional methods in the comparison. The sensitivity analysis also demonstrated that the AI-based approach is sensitive to input parameters such as portfolio size and training period.

The requirement for high-quality financial data is one of the drawbacks of the AI-based method. The predictive model's accuracy is determined by the quality of the data used to train the model. Overfitting is another concern with complicated deep learning models, in which the model learns to fit the training data too closely and performs badly on fresh data.

Future research directions for the AI-based approach include the use of more advanced deep learning models, such as recurrent neural networks and convolutional neural networks, as well as the incorporation of external factors to improve model accuracy, such as news sentiment and macroeconomic indicators. Risk-parity optimization and other optimization strategies could also be investigated.

Finally, the AI-based approach to stock portfolio optimisation has yielded encouraging results and has the potential to improve investment decision-making and portfolio management. However, it is critical to recognise the approach's limitations and hazards, as well as future research areas to increase its accuracy and effectiveness.

8 CONCLUSION

Finally, the application of artificial intelligence (AI) in stock portfolio optimisation has yielded encouraging outcomes in terms of improving investment decision-making and portfolio management. Deep learning models, in particular, have showed the ability to learn complicated patterns in financial data and generate accurate forecasts of future stock values, which can be utilized to optimize the portfolio, in terms of ROI, Sharpe ratio, and volatility, the study's findings show that the AI-based strategy outperforms traditional portfolio optimisation methods. It should be noted, however, that the predictive model's accuracy is greatly dependent on the quality of the financial data used to train the model, and overfitting is a problem with complicated deep learning models.

Despite its shortcomings, the AI-based method to stock portfolio optimisation has enormous potential for future research and improvement. Future research approaches could involve using more advanced deep learning models, incorporating external factors, and experimenting with different optimisation techniques.

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