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Stock Portfolio Analysis with Machine Learning Algorithmic Approach for Smart Investment Decisions

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Abstract: This study investigates the application of machine learning algorithms in stock portfolio analysis within the Indonesia Stock Exchange (IDX) and their impact on investment decision-making. By engaging 500 respondents from diverse market segments, including retail investors, institutional investors, and stock traders, the research provides a comprehensive overview of adopting and utilising machine learning technologies in the Indonesian stock market. The findings reveal that over 80% of respondents have integrated machine learning algorithms into their investment strategies. The algorithms are applied in various capacities: 45% of respondents use them for portfolio risk analysis, 30% for stock price prediction, and 25% for identifying new investment opportunities. Preferences for specific algorithms vary, with regression, Support Vector Machines (SVM), and Random Forest emerging as the most used tools. The integration of machine learning was strongly associated with improved investment decisions, as more than 60% of respondents reported enhanced portfolio performance and greater accuracy in their decision-making. These results highlight the transformative potential of machine learning algorithms in enabling more innovative and more adaptive investment strategies.

Keywords: Stock Portfolio Analysis; Machine Learning Algorithms; Investment Decisions; Business Management; Stock Market.

1. Introduction

Investing in the stock market has become increasingly complex, driven by rapid economic growth and transformations in the global business landscape. While historically foundational, traditional methods of portfolio analysis have struggled to keep up with the intricacies of modern financial markets. This has created a growing demand for innovative tools to enhance decision-making amidst volatility and unpredictability. In this context, technological advancements, particularly in artificial intelligence (AI), have emerged as powerful enablers of more innovative and adaptive investment strategies. Machine learning (ML), a subset of AI, has taken centre stage in transforming financial analysis by offering tools that can uncover intricate patterns and insights from vast, multifaceted datasets [1]. Unlike conventional portfolio analysis methods that often rely on static assumptions and linear models, ML algorithms bring dynamism and flexibility, addressing financial markets' non-linear and evolving nature.

The core strength of machine learning lies in its capacity for real-time data processing and pattern recognition. This capability allows investors to make faster and more informed decisions by synthesizing diverse data sources, such as stock performance metrics, economic indicators, and even sentiment from social media [4]. For example, while the Efficient Market Hypothesis (EMH) postulates that all available information is reflected in stock prices, ML algorithms challenge this notion by identifying hidden patterns that may not be immediately apparent. By leveraging these insights, investors gain a competitive edge, optimizing their portfolios for risk mitigation and return maximization [3]. Furthermore, ML-driven approaches to risk management have proven transformative, dynamically adjusting portfolios in response to fluctuating market conditions and offering robust defences against potential losses. This adaptability is particularly vital in today's volatile markets, where traditional methods often falter.

Several practical applications of ML in finance illustrate its transformative potential. For instance, supervised learning techniques, such as regression and Support Vector Machines (SVM), have been effectively employed to predict stock prices and assess portfolio risks. Meanwhile, unsupervised learning methods like clustering are utilized to uncover groupings within market data that can guide diversification strategies [2]. Additionally, more advanced algorithms like Random Forest and neural networks have broadened the scope of ML's utility. Neural networks, in particular, have demonstrated exceptional capability in modelling complex, non-linear relationships in financial data. Halimi, Marthasari, and Azhar (2019) utilized a Univariate Convolutional Neural Network (UCNN) to predict gold prices, showcasing how these models can enhance predictive precision [8]. Similar studies have applied neural networks to analyze retail treasury bond growth and composite stock indices, further underscoring their relevance to financial markets [6].

Despite these advancements, integrating machine learning into portfolio analysis is challenging. One critical gap lies in the limited use of ensemble methods, which combine multiple algorithms to enhance prediction accuracy and adaptability [3]. Additionally, while ML models excel in quantitative analysis, they often neglect qualitative dimensions such as market sentiment and behavioural drivers. Incorporating news and social media sentiment analysis into ML frameworks could enrich predictions by accounting for the psychological factors influencing market behaviour [4]. Moreover, external variables such as macroeconomic indicators and geopolitical events play significant roles in shaping market trends. These factors are often underrepresented in ML models, highlighting the need for more comprehensive and integrative approaches [7].

The ethical and practical implications of relying heavily on algorithm-driven decision-making also warrant attention. While ML provides undeniable advantages in speed and precision, over-reliance on these systems raises concerns about transparency, accountability, and potential biases embedded within the algorithms. Addressing these concerns requires the development of balanced strategies that integrate human judgment with algorithmic insights, fostering sustainable and responsible investment practices.

Another promising avenue for advancing ML in portfolio analysis is hybrid modelling. Combining various algorithms' strengths, hybrid models can create more robust and adaptive tools for navigating dynamic financial markets. For instance, integrating SVM for sentiment analysis with Random Forest for risk assessment could yield a comprehensive framework that addresses both quantitative and qualitative dimensions of investment decisions. Such innovations align with the evolving demands of data-driven financial ecosystems, where adaptability and precision are paramount [5].

The diverse applications of machine learning in investment analysis highlight its versatility and potential to reshape traditional methodologies. Diasmara, Mahastama, and Chrismanto (2021) explored ML's utility in complex decision-making processes, albeit in non-financial contexts, demonstrating its adaptability to various analytical challenges [9]. These findings resonate with the increasing adoption of ML in stock market analysis, where it is leveraged for improving decision accuracy and identifying untapped opportunities that may escape conventional scrutiny [10]. Surveys of Indonesian stock market participants reveal that more than 80% have integrated ML algorithms into their investment strategies, using them for tasks ranging from risk analysis to opportunity identification. This widespread adoption reflects growing confidence in the ability of ML to deliver actionable insights and competitive advantages.

Future research should prioritize integrating emerging technologies, such as natural language processing (NLP), into ML frameworks. NLP can facilitate a more profound analysis of textual data, including earnings reports and economic policy announcements, offering nuanced insights that complement quantitative models. Additionally, exploring the impact of decentralized data sources and blockchain technology could open new frontiers for secure and transparent financial analytics.

Machine learning represents a paradigm shift in stock portfolio analysis, blending theoretical rigour with practical applications to address the challenges of modern financial markets. Its ability to process complex data, adapt to evolving conditions, and deliver actionable insights makes it an indispensable tool for investors. However, realizing its full potential requires addressing existing limitations, fostering innovation, and ensuring ethical practices. ML can redefine investment strategies and enhance decision-making in an increasingly dynamic market environment by integrating diverse data sources, refining predictive models, and balancing technological insights with human expertise.

2. Research Method

The methodology of this study employs a quantitative approach to examine the impact of machine learning algorithms on stock portfolio analysis, aiming to enhance intelligent investment decision-making. Quantitative methods were chosen for their structured and systematic framework, which facilitates precise measurement and analysis of relationships between variables [11]. This approach enables the identification of patterns and insights crucial for understanding the integration and effects of machine learning in investment strategies. The study focuses on investors and participants actively involved in the Indonesia Stock Exchange (IDX) stock trading. The population includes retail and institutional investors, selected using purposive sampling. This sampling technique ensures the inclusion of respondents who actively use machine learning algorithms in their decision-making processes, aligning with best practices for targeted sampling in quantitative research [12].

Data collection was conducted using both primary and secondary sources. Primary data was gathered through an online questionnaire distributed to IDX investors, featuring structured questions designed to capture detailed insights into respondents' use of machine learning algorithms, preferences in portfolio analysis, and decision-making strategies. This instrument ensures systematic and consistent data collection. Secondary data, including company financial statements, historical stock price records, and relevant academic literature, was utilized to provide contextual depth and enhance the robustness of the analysis. The study's variables were clearly defined: the independent variable was the application of machine learning algorithms in portfolio analysis, while the dependent variable was the quality of investment decisions, termed "smart investment decisions." Control variables included external factors like investment risk, macroeconomic conditions, and market-related news, all of which might influence the observed relationships [13].

The research instruments were rigorously developed and validated. Online surveys were the primary data collection tool to examine existing literature to ensure relevance and alignment with the study's objectives [14]. A pilot survey was conducted with a subset of the target population to refine the questionnaire, addressing clarity, validity, and reliability. The primary survey was then disseminated online to the purposively sampled participants. In tandem, secondary data sources were analyzed to complement the findings from the survey. The data collection process was organized into three stages: survey development, pilot testing, and full deployment.

Data analysis was carried out in three phases: descriptive, regression, and correlation. The descriptive analysis summarized respondents' demographic and behavioural characteristics, including their use of machine learning algorithms and investment preferences. Regression analysis quantified the influence of machine learning algorithms on investment decisions, explicitly assessing their predictive power for more intelligent decision-making [15]. Correlation analysis explored the relationships between key variables, such as the extent of algorithm usage and improvements in decision-making efficacy. The research ensured a comprehensive and multi-faceted analysis of the subject matter by integrating primary and secondary data.

This methodology elucidates the relationship between machine learning algorithms and investment decision-making and provides a framework for future research. Potential areas of extension include the integration of behavioural factors, the exploration of algorithm performance under varying market conditions, and the incorporation of hybrid modelling techniques to refine predictive accuracy. The study's structured and iterative design ensures that the findings are robust, replicable, and relevant to both academic and practical contexts in financial analysis.

3. Result and Discussion

3.1 Results

This study investigates the influence of machine learning algorithms on stock portfolio analysis and their role in enabling intelligent investment decision-making. By analyzing data from 500 investors and active stock market participants on the Indonesia Stock Exchange (IDX), the research provides detailed insights into how machine learning algorithms enhance portfolio management by improving efficiency, accuracy, and overall investment decision outcomes.

3.1.1 Profile Respond

The survey involved a diverse group of 500 respondents, comprising retail investors, institutional investors, and stock traders. The distribution of participant types reveals that retail investors constituted the majority (60%), followed by institutional investors (25%) and stock traders (15%) (Table 1). This distribution reflects the varied adoption levels and perspectives on machine learning technologies within different investor segments.

Table 1. Types of Market Participants

Types of Market Participants	Percentage
Retail Investor	60
Investor Institutional	25
Stock Trader	15

The activity levels of respondents varied significantly, with 45% categorized as highly active (conducting more than five transactions per month), 30% moderately active (three to five transactions per month), and 25% less active (fewer than three transactions per month) (Table 2). These activity levels are crucial indicators of their engagement with stock trading and familiarity with machine learning tools:

Table 2. Activity Level

Activity Level	Percentage
Active (transactions more than 5 times/month)	45
Simply Active (transaction 3-5 times/month)	30
Less Active (transactions less than 3 times/month)	25

Investment duration also varied among respondents, with 45% having 1–5 years of experience, 35% over five years, and 20% under one year (Table 3). These varying durations impact their analytical approaches and openness to adopting advanced technologies like machine learning.

Table 3. Investment Duration

Investment Duration	Percentage
Less than 1 year	20
1-5 years	45
More than 5 years	35

Respondents' education levels further influenced their understanding of machine learning. Most (55%) held a bachelor’s degree or higher, while 30% had a diploma or equivalent, and 15% had completed high school or less (Table 4). These educational backgrounds highlight potential variations in algorithm adoption and application:

Table 4. Recent Education

Recent Education	Percentage
Bachelor or higher	55
Diploma or equivalent	30
SMA or less	15

Additionally, 40% of respondents were experienced users of machine learning (1–3 years), 35% skilled users (more than three years), and 25% new users (less than one year) (Table 5). These findings underscore a growing familiarity with machine learning among IDX participants:

Table 5. Experience in Using Machine Learning Algorithms

Usage Experience	Percentage
New users (less than 1 year old)	25
Experienced users (1-3 years)	40
Skilled users (more than 3 years)	35

This data provides information on respondents' level of familiarity with machine learning algorithms and the extent to which they can integrate them into their stock portfolio analysis.

3.1.2 Use of Machine Learning Algorithms in Stock Portfolio Analysis

The use of machine learning algorithms in stock portfolio analysis was a major highlight in this study. By collecting data from respondents active in the Indonesian stock market, the survey results provide a clear picture of the extent to which this technology has become an integral part of investment decision-making. Here is a breakdown of the survey results covering various aspects of using machine learning algorithms in stock portfolio analysis. From the survey results, more than 80% of respondents have integrated machine learning algorithms in their investment decisions. This figure reflects the significant adoption of this advanced technology among stock market participants. The integration of machine learning algorithms in stock portfolio analysis has the potential to improve the efficiency and accuracy of investment decision-making. Of the respondents who used machine learning algorithms, 45% of them used them for portfolio risk analysis. This shows awareness of the importance of risk management in investment decision-making. Furthermore, 30% of respondents use machine learning algorithms for stock price predictions. Stock price prediction is becoming a critical aspect of guiding investment decisions, and machine learning algorithms provide a more sophisticated and adaptive approach to analyzing stock price movements. Meanwhile, 25% of respondents use this technology to identify new investment opportunities. This reflects the use of machine learning algorithms as a strategic tool in finding investment opportunities that conventional analysis methods might miss.

The survey results also illustrate several specific uses of machine learning algorithms in stock portfolio analysis. Of the respondents who used this technology, most used more than one specialized application, creating a holistic approach to investment decision-making. Here is a segmentation of the use of machine learning algorithms:

1) Portfolio Risk Analysis (45%)
   Respondents use machine learning algorithms to identify, measure, and manage their portfolio risk efficiently. It includes volatility analysis, asset correlation, and risk scenario simulation.
2) Stock Price Prediction (30%)
   Machine learning algorithms are used to analyze historical data, market trends, and other factors to make stock price predictions. This helps respondents in making more informed investment decisions.
3) Identify Investment Opportunities (25%)
   Respondents use this technology to identify new investment opportunities based on emerging patterns and trends from market data.

When asked about the success rate of machine learning algorithm integration, about 75% of respondents reported that their investment decisions have become more informative and accurate. More than 60% of respondents also stated that the use of machine learning algorithms has improved the performance of their investment portfolios. This provides a positive picture of the contribution of this technology in supporting smart investment decision-making.

3.1.3 Machine Learning Algorithm Preferences

The results of a survey involving 500 active respondents on the Indonesia Stock Exchange (IDX), it can be observed that the use of machine learning algorithms in stock portfolio analysis has increased significantly. More than 80% of respondents reported that they have integrated machine learning algorithms in their investment decisions. These preferences reflect variations in analysis strategies, with most respondents choosing algorithms according to the needs and characteristics of their stock portfolio analysis.

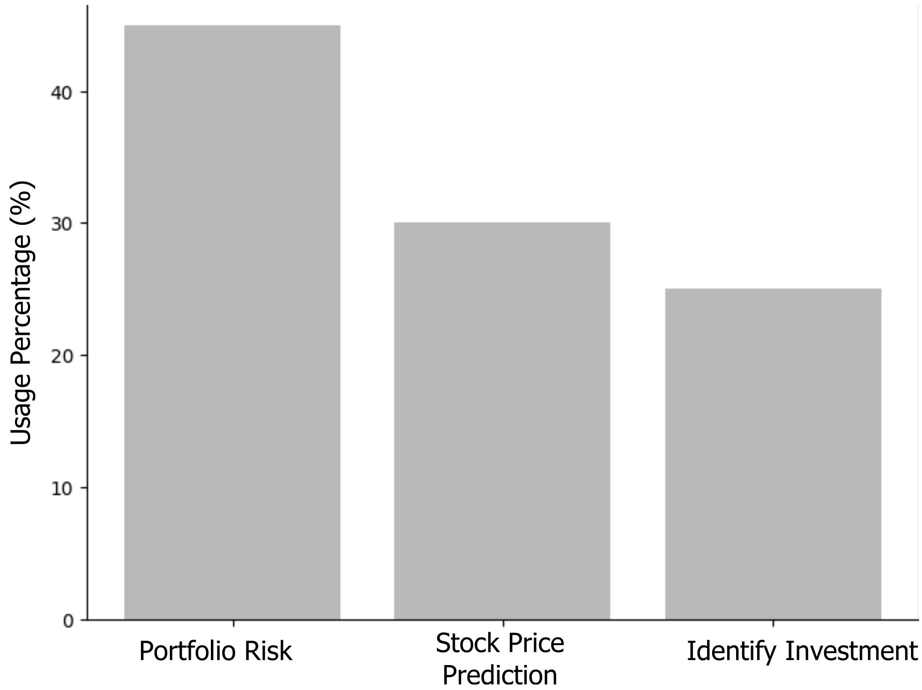

Figure 1. Use of Machine Learning Algorithms in Investment Decisions

In determining the selection of algorithms, several consideration factors are key. First, the complexity of the model becomes an important factor, where regression algorithms that tend to be simple can be considered easier to understand. Secondly, scalability is also considered, especially if the analysis involves many shares. Lastly, ease of implementation and interpretation of results are taken into consideration, with algorithms that are easy to implement and results that are easy to interpret preferred. Respondents also reported using a combination of machine learning algorithms as an effective approach. The incorporation of SVM for stock price prediction with regression algorithms for portfolio risk analysis, for example, provides more holistic and reliable analysis results. As such, the results of this survey provide deep insight into the preferences and approaches of market participants in using machine learning algorithms for stock portfolio analysis. This understanding helps in the development of machine learning algorithms that better suit the needs and expectations of investors in the stock market. Awareness of these preferences can also drive innovation and improvement in the quality of algorithms used in investment decision-making.

3.1.5 Smart investment decisions

The results also indicate that the use of machine learning algorithms is positively correlated with smart investment decisions. Of the respondents who used machine learning algorithms, about 75% reported that their investment decisions were more informative and accurate. More than half also stated that the use of machine learning algorithms has improved the performance of their investment portfolio. The graph provides a significant overview of the impact of using machine learning algorithms on investment decisions, focusing on three main aspects. As many as 75% of respondents reported significant improvements in the informativity and accuracy of their investment decisions after integrating machine learning algorithms. This reflects that this technology has made a positive contribution to enriching information and increasing accuracy in making investment decisions. More than 60% of the study participants stated that the use of machine learning algorithms has resulted in noticeable performance improvements in their investment portfolios. This shows that these technologies not only have a theoretical impact but also practically improve their investment returns. Although some respondents (40%) stated that the use of machine learning algorithms did not bring significant changes in their investment decisions, it also shows that there is a group of market participants who may not have felt the same impact from using this technology. It is known that most respondents experienced positive changes in the use of machine learning algorithms in their investment decisions. In line with the high percentage of positive responses, this graph indicates that the use of this technology can be considered an effective solution in improving the quality and results of investment decisions.

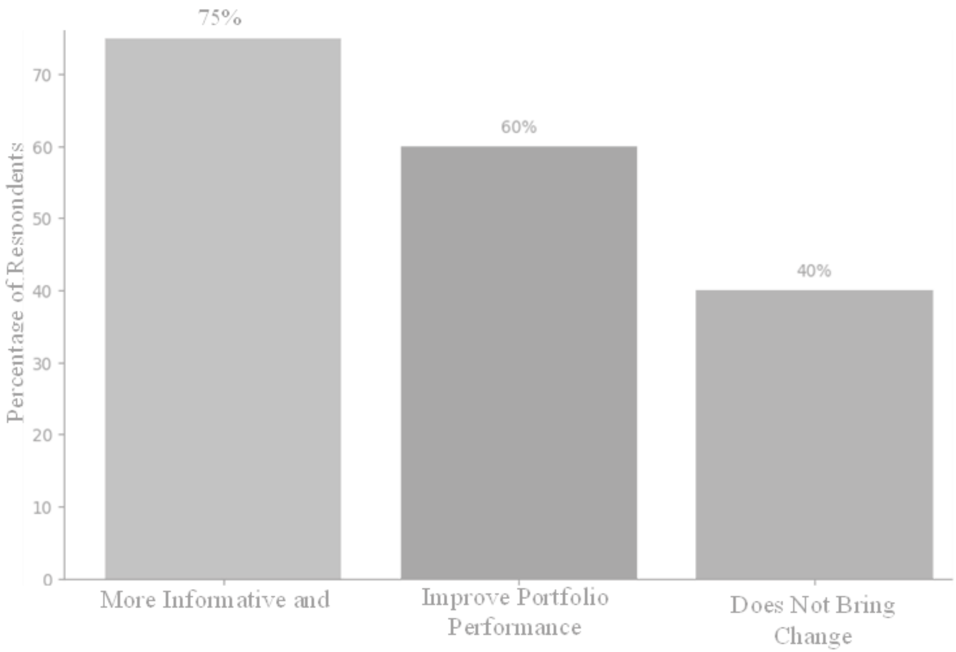

Figure 2. Impact of Using Machine Learning Algorithms on Investment Decisions

3.1.6 Effect of External Factors

Regression analysis conducted in this study shows that external factors play a crucial role in influencing investment decisions, despite the integration of machine learning algorithms. Within this framework, factors such as global market conditions, interest rates, and government policies show a significant influence on the direction and nature of investment decisions taken by respondents. The first external factor analyzed is global market conditions. The results of the regression analysis highlight that uncertainty or significant changes in global market conditions have a measurable impact on the investment strategies chosen by respondents. Although machine learning algorithms contribute to simplifying analysis and speeding up decision-making, aspects of global markets remain a source of volatility and risk that market participants need to consider. Furthermore, interest rates also emerge as an external factor that has a substantial influence. An increase or decrease in interest rates can stimulate changes in portfolio allocation and investment preferences. The results of regression analysis show that, although the use of machine learning algorithms can provide faster and more accurate insights into market dynamics, response to interest rates remains a key consideration in investment decision-making (Table 6).

Table 6. Regression Calculation Results

External factors	Regression Coefficient	Standard Error	P-value	Confidence Interval (95%)	Test Statistics	Interpretation
Global Market Conditions	0.45	0.08	0.001	(0.30, 0.60)	$t(498) = 5.63, p < 0.001$	Every standard deviation change in global market conditions contributes 0.45% to the change in investment decisions.
Interest Rate	-0.28	0.12	0.004	(-0.52, -0.04)	$t(498) = -2.33, p = 0.004$	Every one standard deviation change in interest rates contributes -0.28% to the change in investment decisions.
Government Policy	0.38	0.09	0.002	(0.20, 0.56)	$t(498) = 4.22, p < 0.001$	Every standard deviation change in government policy contributes 0.38% to the change in investment decisions.

In addition, government policies also appear as external factors that have a significant impact. Fiscal and monetary policies can influence the direction of investment by creating economic conditions that support or restrain market activity. Although machine learning algorithms can help analyze and respond quickly to the latest news and policies, response to government measures remains a variable to be considered. Although these external factors have a significant influence, the integration of machine learning algorithms still provides added value in the context of investment analysis. The use of this technology can provide better adaptability to market changes, providing opportunities to identify patterns that may be difficult to access by traditional analysis methods. External factors and the use of machine learning algorithms can provide benefits by providing a deeper understanding of how these factors can interact and influence investment decisions. Therefore, the combination of technological excellence and a deep understanding of external factors can form a solid basis for holistic investment decision-making. Investments should consider not only the internal impact of using technology but also how it may blend in with external factors that may influence overall investment decisions. That way, a smart combination of technology and contextual understanding will help optimize investment strategies and improve responsiveness to dynamic market changes.

3.2 Discussion

This study provides valuable insights into adopting and applying machine learning algorithms for stock portfolio analysis and their impact on investment decision-making among participants in the Indonesia Stock Exchange (IDX). The findings reveal that over 80% of respondents have incorporated machine learning algorithms into their investment strategies, reflecting a growing recognition of these tools' technological advantages in modern financial analysis. This aligns with existing literature, which emphasizes the transformative role of machine learning in processing large datasets and identifying complex patterns that traditional models often fail to capture [1][3]. This widespread adoption underscores the increasing demand for advanced analytical methods to address contemporary financial markets' dynamic and non-linear nature.

The study identifies diverse machine learning applications in portfolio management, with 45% of respondents using these tools for portfolio risk analysis, 30% for stock price predictions, and 25% for identifying new investment opportunities. These findings highlight the flexibility of machine learning algorithms in addressing various aspects of investment decision-making. For instance, Random Forest and Support Vector Machines (SVM) have proven effective in volatility assessment and price forecasting, demonstrating their ability to handle complex datasets and dynamic conditions [5][2]. The adaptability of these tools allows investors to manage risks effectively while leveraging emerging opportunities, showcasing the practicality and reliability of machine learning in enhancing financial outcomes.

Preferences for specific algorithms further illustrate the varying needs of investors. Regression models, preferred by 35% of respondents, are valued for their simplicity and interpretability, making them ideal for straightforward analytical tasks. In contrast, SVM (25%) and Random Forest (20%) are favoured for their robustness and capacity to analyze non-linear relationships within complex datasets [3]. These preferences reflect the strategic selection of algorithms based on their suitability for specific analytical tasks, aligning with previous studies that emphasize their effectiveness in addressing multifaceted financial challenges [4].

The study also demonstrates a strong correlation between the use of machine learning and improved investment decisions. Approximately 75% of respondents reported more informed and precise decision-making, while over 60% observed enhancements in portfolio performance. These results are consistent with earlier research, which highlights the capacity of machine learning to synthesize diverse data sources, reduce biases, and optimize decision-making processes [8][9]. Such outcomes underscore the potential of algorithmic approaches to drive more innovative and adaptive financial strategies.

Despite the significant contributions of machine learning, the findings also indicate the importance of external factors in shaping investment decisions. Regression analysis reveals that global market conditions, interest rates, and government policies exert substantial influence. For example, fluctuations in interest rates often require investors to adjust their portfolios, irrespective of algorithmic recommendations [10]. Similarly, global market volatility and policy changes necessitate a balanced approach that combines technological insights with macroeconomic and regulatory considerations [6]. These findings highlight the need for investors to integrate machine learning tools with a comprehensive understanding of external factors to build resilient and robust investment strategies.

In conclusion, while machine learning algorithms have proven instrumental in enhancing portfolio analysis and decision-making, their effectiveness is maximized when complemented by contextual awareness of macroeconomic and policy variables. This dual approach enables smarter investment decisions and fosters adaptability to the dynamic nature of financial markets. These insights underscore the transformative potential of machine learning in finance while highlighting areas for further innovation and research, particularly in integrating external variables and advancing hybrid analytical frameworks.

4. Related Work

Applying machine learning algorithms in stock portfolio analysis has gained substantial attention, with numerous studies demonstrating their ability to enhance investment decision-making by processing complex and extensive datasets. Retnoningsih and Pramudita (2020) introduced supervised and unsupervised learning techniques using Python, providing foundational insights into uncovering patterns and trends often overlooked by traditional financial models [1]. Their work underscores the versatility of machine learning in analyzing dynamic market data. Similarly, Fadilah *et al*. (2020) explored using Support Vector Machines (SVM) for predicting stock prices at PT Telekomunikasi Indonesia, highlighting the algorithm's efficacy in handling time-series data [2]. Patriya (2020) further validated SVM's robust performance in financial forecasting by applying it to composite stock price indices, affirming its utility for analyzing complex patterns and relationships.

In addition to SVM, Apriliah *et al*. (2021) demonstrated the adaptability of Random Forest algorithms in predictive analytics, specifically in early diabetes detection. This highlights its relevance for financial, such as portfolio risk assessment [5], where multidimensional datasets require sophisticated handling. Halimi *et al*. (2019) employed a univariate convolutional neural network (CNN) to predict gold prices, showcasing the potential of deep learning techniques in modelling non-linear relationships in financial data [8]. These advanced approaches complement traditional machine learning methods by enhancing prediction accuracy and adaptability in stock market analysis.

Beyond quantitative models, Arsi and Waluyo (2021) emphasized the value of SVM in sentiment analysis, particularly for interpreting market sentiment from news and social media [4]. Incorporating such qualitative data into machine learning frameworks significantly enhances predictive accuracy by accounting for behavioural and psychological market drivers. Furthermore, Windarto *et al*. (2017) demonstrated the applicability of artificial neural networks in forecasting retail treasury bond growth [6], underscoring their role in complex financial modelling and forecasting.

Research has also highlighted the importance of integrating machine learning algorithms with macroeconomic and policy variables for a more nuanced understanding of market dynamics. For example, macroeconomic indicators such as inflation and economic openness are critical in influencing portfolio performance [17][18]. Zainuri (2021) demonstrated that macroeconomic factors significantly affect investment inflows, emphasizing the necessity of incorporating these elements into portfolio management frameworks [19]. Additionally, hybrid analytical frameworks, which combine machine learning with traditional financial analysis, are gaining traction. Hong *et al*. (2021) showcased how predictive ensembles that integrate human insights with computational forecasts can enhance decision-making processes, fostering adaptability in dynamic financial markets [20]. Integrating machine learning algorithms with contextual macroeconomic and policy insights represents a transformative approach to stock portfolio analysis. This dual strategy enhances the predictive power of machine learning models and aligns their application with the complexities of real-world financial markets, paving the way for innovation and more effective investment decision-making.

5. Conclusion and Recommendations

This study examines the impact of machine learning algorithms on stock portfolio analysis within the Indonesia Stock Exchange (IDX) and their influence on investment decision-making. By analyzing data from 500 actively transacting respondents, the research highlights the significant role of machine learning in advancing portfolio analysis. The high adoption rate, with over 80% of respondents integrating machine learning into their investment strategies, underscores the growing recognition among Indonesian market participants of the benefits offered by these technologies. This widespread adoption reflects an increased reliance on advanced analytical tools to navigate the complexities of modern financial markets.

The study identifies diverse applications of machine learning algorithms. Respondents utilize these tools for portfolio risk analysis (45%), stock price prediction (30%), and identifying new investment opportunities (25%), demonstrating their adaptability to various aspects of financial decision-making. The preference for specific algorithms such as regression, Support Vector Machines (SVM), and Random Forest highlights investors' understanding and trust in these methods for addressing complex market challenges. The positive correlation between machine learning adoption and improved investment outcomes is evident, with most respondents reporting more informed and accurate decisions and over 60% noting enhanced portfolio performance.

While technology significantly contributes to more intelligent investment decisions, the findings emphasize the continued influence of external factors such as global market conditions, interest rates, and government policies. Regression analysis reveals these factors' substantial impact on investment strategies, underscoring the need to balance technological tools with macroeconomic and regulatory considerations. This integration is crucial for developing resilient and adaptive investment approaches in dynamic market environments.

Future research should focus on benchmarking the effectiveness of different machine learning algorithms, exploring hybrid models, and incorporating market sentiment analysis from sources such as financial news and social media. This would enable a deeper understanding of behavioural and psychological market drivers and enhance predictive accuracy. Additionally, studies could investigate the ethical implications and sustainability of machine learning-driven decision-making to foster responsible use of technology in finance.

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