International Journal of Management and Sustainability
2025 Vol. 14, No. 3, pp. 964-981
ISSN(e): 2306-0662
ISSN(p): 2306-9856
DOI: 10.18488/11.v14i3.4426

Bridging finance and technology: Machine learning-based portfolio construction in the Indonesian market

Zabrina Raissa[1+]
Hendrawan Supratikno[2]
Edison Hulu[3]
Sung Suk Kim[4]

[1,2,3,4]*Faculty of Economics and Business, Pelita Harapan University, Indonesia.*
[1]*Email: 01617210008@student.uph.edu*
[2]*Email: hendrasupra@yahoo.com*
[3]*Email: hulu.edison@yahoo.com*
[4]*Email: Sungsuk.kim@uph.edu*

(+ Corresponding author)

Article History
Received: 19 May 2025
Revised: 26 August 2025
Accepted: 18 September 2025
Published: 29 September 2025

Keywords
Financial decision-making
Investment strategy
Machine learning applications
Macroeconomic analysis
Portfolio management.

ABSTRACT

This study investigates the effectiveness of machine learning models in forecasting stock prices and constructing investment portfolios, with a specific focus on the integration of macroeconomic and technical indicators in the Indonesian stock market. Using Random Forest, Support Vector Regression, and Bagging models, the study forecasts three-month-ahead stock prices for 33 large-cap Indonesian firms, covering the period from 2022 to 2024. Forecast accuracy is evaluated using MAE, RMSE, and MAPE, while portfolio performance is assessed based on returns and risks, benchmarked against both traditional methods and key Indonesian indexes. Model interpretability is further enhanced through the use of SHAP, which helps identify the influence of individual variables on the predictions. Results show that machine learning models incorporating macroeconomic and technical indicators are able to effectively forecast long-term stock prices with strong predictive performance. Portfolios constructed using machine learning forecasts, particularly those weighted using mean-variance and inverse MAPE strategies, outperformed traditional benchmarks in terms of return at maturity. Furthermore, SHAP analysis reveals that macroeconomic indicators, particularly global market indices and bond yields, have a stronger influence on stock price predictions than most technical indicators, with the 3-month EMA being the only technical indicator with consistent predictive value. These findings demonstrate the practical value of integrating macroeconomic context into predictive modeling and highlight the potential of machine learning-driven strategies for investors seeking adaptable portfolio solutions. However, the study is limited to a single market and quarter; future research may extend the framework to broader settings to validate its generalizability.

Contribution/Originality: This study integrates macroeconomic indicators into machine learning–based stock forecasting and portfolio construction, offering a novel approach within an emerging market context. By applying SHAP for model explainability, it enhances transparency for investors. Overall, the findings support more adaptive, data-driven investment strategies suited to the conditions of emerging markets.

1. INTRODUCTION

The equity capital market is a financial platform where companies, institutions, or issuers raise funds by offering ownership stakes to investors, referred to as stocks. Investors generally prefer equity investments over other investment forms due to several factors, including easier access to market information, faster transactions driven by the liquidity of equity investments, and potentially higher returns than traditional investment options (Chang & Huang, 2024; Tursunbaevich, 2020). However, this advantage also comes with its own risks and limitations, notably greater exposure to market volatility, leading to higher risks associated with equity investments. There are several strategies to overcome these challenges (Albahli et al., 2022), with portfolio diversification recognized as one of the most impactful methods (Migliavacca, Goodell, & Paltrinieri, 2023). The main idea behind this method is the process of selecting the right combination of assets that balances the risks and rewards associated with the portfolio, aiming to suit each investor's investment goals. As a result, quantitative models and data-driven techniques have become increasingly relevant in guiding portfolio construction decisions (Wu, 2023).

Quantitative investment techniques are capable of modeling and forecasting stock price movements, aiming to assist investors in responsible and data-driven decision-making (Du & Shen, 2024). Over the years, many forecasting methods have been developed with the goal of achieving strong predictive accuracy (Kumbure, Lohrmann, Luukka, & Porras, 2022; Shah, Vaidya, & Shah, 2022; Sonkavde et al., 2023). Among the earliest and most widely adopted approaches are statistical time series models, also known as econometric models, such as Autoregressive Integrated Moving Average (ARIMA), ARIMA-GARCH, Seasonal ARIMA (SARIMA), and others (Bagalkot, Dinesha, & Naik, 2024; Saleh Ahmar, Singh, Van Thanh, Viet Tinh, & Minh Hieu, 2022). However, Almaafi, Bajaba, and Alnori (2023) suggest that traditional econometric models may lack the capability to effectively capture the dynamic and complex nature of stock prices. Hence, with technological advancement, the application of machine learning (ML) and deep learning (DL) models in financial modeling has gained significant traction in recent years, often outperforming traditional econometric techniques in terms of predictive performance (Berger & Koubová, 2024; Kheimi, Almadani, & Zounemat-Kermani, 2024; Latif, Selvam, Kapse, Sharma, & Mahajan, 2023).

Despite extensive research on stock price modeling using ML and DL, most studies still predominantly rely on historical stock prices and standard technical indicators. Therefore, a clear and relevant research gap can be identified: the limited integration of macroeconomic indicators into ML-based predictive frameworks particularly in the context of emerging markets such as the Indonesian capital market despite previous studies demonstrating meaningful relationships between these variables. For example, Khan, Teng, Khan, and Khan (2023) utilized an Autoregressive Distributed Lag (ARDL) model to examine the impact of oil prices, gold prices, and exchange rates on the Shanghai Stock Exchange. They found that oil and gold prices had a positive influence, while exchange rates showed a negative effect over both short- and long-term horizons. Similarly, Hashmi and Chang (2023) applied ARDL and Quantile ARDL (QARDL) techniques to assess the effects of macroeconomic factors on E7 stock indices, identifying foreign direct investment (FDI), trade balance, and the industrial production index (IPI) as significant long-run determinants. These findings are further supported by Prasad, Bakhshi, and Seetharaman (2022), who also reported positive relationships between macroeconomic indicators and stock market volatility, as measured by the VIX index.

In the context of portfolio selection, ML techniques have shown considerable potential in enhancing outcomes (López De Prado, Simonian, Fabozzi, & Fabozzi, 2025). Pinelis and Ruppert (2022) demonstrated that integrating ML into portfolio selection leads to statistically and economically significant gains. However, most of these ML-integrated portfolios are constructed using data from well-established markets, which may not reflect the unique characteristics of the Indonesian capital market. As a developing country, Indonesia presents a distinct set of challenges, such as heightened market volatility and unpredictable investor behavior (Annaufal, Mariyana, & Roostika, 2024). This points to another research gap identified in previous studies, emphasizing the importance of tailoring ML-based portfolio selection strategies to the local market context.

Thus, this study aims to address two key research gaps. The first concerns the limited integration of macroeconomic indicators into machine learning-based stock price prediction models, particularly within the Indonesian context. The second relates to the scarcity of research applying machine learning techniques to portfolio construction in Indonesia's capital market. To bridge these gaps, this study proposes a two-stage approach. First, it forecasts the three-month-ahead closing prices of Indonesian stocks by incorporating historical data, technical indicators, and macroeconomic variables, using machine learning models such as Random Forest, Support Vector Machine, and the ensemble learning method Bootstrap Aggregating (Bagging). The resulting forecasts are then used to construct a machine learning-enhanced investment portfolio tailored to the Indonesian market. This portfolio's performance is evaluated against key Indonesian stock market benchmarks, including IDXV30, IHSG, IDX30, and LQ45. Additionally, to enhance model interpretability, this study employs Shapley Additive Explanations (SHAP), a method under the eXplainable AI (XAI) framework, to explore and explain the influence of each input variable on the model's predictions and support the examination of the proposed hypotheses.

The findings of this study offer both theoretical and practical contributions. Theoretically, this research addresses the gaps identified in previous studies, namely, integrating macroeconomic indicators into machine learning-based predictive modeling of stock prices and applying machine learning-integrated strategies for portfolio construction within the Indonesian capital market. Practically, the results could assist investors and financial institutions in developing data-driven investment strategies, particularly in emerging markets such as Indonesia, where traditional econometric models may fall short of capturing the complex and volatile patterns of stock movements. Furthermore, the results also provide insights into how each indicator influences stock price movements, leading to an increased understanding of how these variables can be used to support more strategic investment decisions. In doing so, this research enriches the existing body of knowledge on predictive modeling in the field of investment analysis.

2. LITERATURE REVIEW

2.1. Investment Time Frames

Investment time frames are a critical component of investment strategies, which shape an investor's analytical approach and overall risk profile. The time frames, ranging from medium to long-term, are determined based on individual goals and risk tolerance. Two of the most widely adopted time frames include long-term and medium-term investing. Long-term refers to the act of holding assets for several years with the expectation of gradual returns, and conversely, medium-term refers to shorter periods of time, such as three to twelve months. Quarterly rebalancing is often performed for medium-term strategies to adjust for market dynamics.

The rebalancing frequency of a portfolio has significant implications for the performance results of momentum portfolios. Raju (2024) indicates that rebalancing frequencies are usually defined in months, and researchers typically prefer monthly data in their studies. Furthermore, Jegadeesh and Titman (1993) found higher returns for long/short portfolios using a quarterly rebalancing frequency and a look-back period of 12 months with a short holding period. If rebalancing occurs more frequently, it may be more effective in capturing the effects of persistent momentum across different market conditions.

2.2. Evolution of Portfolio Theory

Causes for the continued evolution of portfolio theory can be found in the effort to develop enhanced and improved strategies for asset allocation and risk management. Beginning with Markowitz (1952), Modern Portfolio Theory (MPT) made diversification a key pillar of the theory of maximizing returns for a given level of risk. As a result, MPT has found widespread application; however, it is based on some ideal assumptions, such as market efficiency and stable correlations, which make it difficult to apply in truly dynamic and information-imperfect markets. Follow-up models like Sharpe's Single Index Model introduced further simplification by establishing a benchmark against which securities could be evaluated relative to a single market index. The computational burden was thus lessened, allowing for easier risk-return evaluations, albeit still within a relatively inflexible structure.

Subsequent developments did refocus attention on the limitations of a single-factor model. The 1970s saw the birth of the Arbitrage Pricing Theory (APT), from which came the rationale for considering multiple macroeconomic factors as important in explaining asset returns. Tools, such as Vector Autoregressive (VAR) models, are utilized to establish such relationships. The Elton and Gruber Model, on the other hand, introduced refinements to the construction of portfolios by accounting for asset covariances, thereby enabling better performance during uncertain market conditions, such as during the COVID-19 pandemic (Manurung, Sinaga, & Manurung, 2023). The Behavioural Portfolio Theory (BPT), on the contrary, provides evidence that investors' decision-making is significantly influenced by cognitive biases, resulting in layered portfolios aimed at hedging against risks and achieving aspirational goals. However, these insights, while revealing, are not conducive to empirical applications due to their relatively low quantitative precision.

Each portfolio management theory provides distinct value but faces obstacles in addressing modern market complexities. The addition of machine learning to portfolio development creates a valuable solution that improves both forecast precision and flexibility. This research aims to expand on existing literature through the integration of machine learning and conventional portfolio theory, including the Markowitz model, to test how their combination affects investment success within the Indonesian capital market. Thus, the following hypothesis is proposed:

H_1: Machine learning-integrated portfolios can yield better returns at maturity than traditional methods.

2.3. Technical Analysis

Investors and traders primarily rely on two analytical approaches to guide their buy and sell decisions: fundamental analysis and technical analysis. Both aim to evaluate and anticipate shifts in supply and demand, which underpin price movements in financial markets. The majority of machine learning applications in stock price prediction have focused on technical analysis, leveraging historical price data and indicators derived from past movements. Technical analysis is grounded in several key assumptions: (1) prices reflect all market dynamics through supply and demand; (2) prices move in identifiable trends; (3) shifts in supply and demand lead to trend reversals; (4) these shifts are detectable through chart patterns; and (5) historical patterns tend to repeat over time. Technical indicators are effective in recognizing certain trends that could signal movements in stock prices. Among the most commonly used technical indicators are the Exponential Moving Average (EMA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD). This research further investigates the forecasting abilities of technical indicators incorporated within a machine learning model. Hence, the following research hypotheses are proposed:

H_2: EMA has a positive linear relationship with future stock prices.

H_3: RSI has a positive linear relationship with future stock prices.

H_4: MACD has a positive linear relationship with future stock prices.

2.4. Macroeconomic Studies

There has been extensive research regarding the relationship between macroeconomic indicators and stock market performance. Assagaf, Murwaningsari, Gunawan, and Mayangsari (2019) found a significant influence from macroeconomic variables such as inflation, interest rates, money supply, and exchange rates on the performance of companies listed on the Indonesia Stock Exchange. Similarly, Laichena and Obwogi (2015) also uncovered a strong association between macroeconomic indicators and stock returns in East African markets, with the USD exchange rate in particular playing a significant role. This finding aligns with how the USD exchange rate functions, as a higher exchange rate can reduce export demand, thus negatively affecting sales and corporate earnings; however, it could also improve profit margins by lowering the cost of imported inputs.

Other macroeconomic factors that could influence local stock price movements are international stock indices, such as the Dow Jones Industrial Average (DJIA), Nikkei 225, Hang Seng Index (HSI), and FTSE 100. However, many previous studies that delved into the intricacies of this impact found mixed results. For example, Rachmawati and Fadila (2024) discovered that the DJIA significantly impacts the performance of Indonesia's Composite Stock Price Index (IHSG), whereas Yuliarta and Bebasari (2023) found no significant impact between them. Similarly, Santoso et al. (2023) found a significant impact from the FTSE 100 Index on IHSG, contrasting the findings of Mie (2014), who found no such impact. These discrepancies further motivate the use of macroeconomic indicators in this study, with the aim of shedding light on how these indicators influence Indonesia's capital market. The Nikkei 225 Index is also found to play a role in influencing IHSG, as reported by Nasution, Rujiman, and Tanjung (2023).

Specifically, the Nikkei 225 exhibits a significant negative long-term impact on IHSG, but no short-term effect is reported. This aligns well with the fact that Japan is a major importer of Indonesia's energy commodities, such as petroleum and coal.

Indonesian government bonds (Surat Utang Negara/SUN) are also essential instruments for attracting foreign investment and fostering sustainable national development. Since the Asian financial crisis in 1997 and the global subprime mortgage crisis, bonds have been recognized as Indonesia's primary source of long-term financing by the government to support financial resilience (Santosa & Sihombing, 2015; Sihombing, Siregar, Manurung, & Santosa, 2014). The relationship between the stock index and bond yields, however, remains subject to debate. While some findings suggest a positive correlation, where increases in the stock index lead to rising yields across bond tenors (Rosanti, 2021), other studies present the opposite. Sundoro (2018) observed that rising stock indices are associated with declining yields across all maturities. These mixed results may reflect varying investor sentiment. During periods of market instability, government bonds are often viewed as safer investment alternatives. Zhou and Meng (2023) support this view, noting that bonds serve as a safe haven during financial turbulence. Similarly, Gulko (2002) found that equities and bonds can exhibit a positive relationship driven by broader macroeconomic conditions. Thus, based on the literature and observed patterns, we propose the following hypotheses:

H_5: USDIDR has a negative linear relationship with future stock prices.

H_6: DJI has a positive linear relationship with future stock prices.

H_7: HSI has a positive linear relationship with future stock prices.

H_8: The Nikkei 225 has a positive linear relationship with future stock prices.

H_9: FTSE has a positive linear relationship with future stock prices.

H_{10}: SUN has a negative linear relationship with future stock prices.

2.5. Indonesian Market Benchmarks

Several key Indonesian indices are utilized in this study as benchmarks, aiming to provide a market-wide comparison against the performance of machine learning-integrated portfolios. The indices consist of the IDX Value30, LQ45, IDX30, and the Indonesia Composite Index (IHSG). The IHSG reflects the overall Indonesian stock market movement and is thus sensitive to various factors, such as global economic shifts and volatile investor sentiment. The LQ45 Index comprises 45 stocks that meet certain criteria, such as substantial market capitalization and high liquidity, among others. IDX30 is very similar to LQ45, as it represents the performance of 30 highly liquid stocks with large market capitalization and is widely used as a market proxy by investors (Verkino, Sinaga, & Andati, 2020). On the other hand, the IDX Value30 (IDXV30) filters its stocks based on valuations, trading volumes, and transactional liquidity. In the field of portfolio construction, the main challenge that investors face is selecting the right combination of stocks, as highlighted by Tanto and Kurniawan (2022), emphasizing the importance of using local market indices as benchmarks for guidance in stock selection. Therefore, the following hypothesis is proposed:

H_{11}: Machine learning-integrated portfolios can yield better returns at maturity than Indonesian market benchmarks.

3. MODELS, METHODOLOGY AND DATA

3.1. Research Model

In this study, a two-stage quantitative methodology is used to evaluate the predictive capability of machine learning models that incorporate macroeconomic indicators and to examine their applicability for portfolio construction. The first stage focuses on developing, validating, and evaluating the predictive capabilities of the models for Indonesian stock prices. However, to ensure that the data is aligned for machine learning modeling, a series of data pre-processing steps are performed, including data cleaning, transformation, train-test splitting, and feature scaling. Once this is completed, a feature selection process based on Random Forest's built-in feature importance scores is conducted to identify the most significant input variables for each stock. The selected models are then trained on both the entire feature set and the reduced feature set to assess the differences in forecasting performance. Hyperparameter optimization, using Grid Search and 10-Fold Cross-Validation, is performed on the selected model to ensure robustness in model performance, with all hyperparameters individually tuned to the unique characteristics of each stock.

The second stage of the methodology focuses on applying the best-performing models to forecast stock prices, which are then used as inputs for portfolio construction. Specifically, the optimal model and its associated hyperparameters, identified during the first stage, are used to generate three-month-ahead forecasts for each stock. Based on these predicted returns, the Sharpe Ratio for each stock is calculated to assess risk-adjusted performance. An ML-integrated portfolio is then constructed by selecting stocks with a Sharpe Ratio that exceeds 1. To assess comparative performance, this portfolio is evaluated against a traditional benchmark portfolio, specifically the Markowitz model, along with several key Indonesian stock indices, namely IHSG, IDX30, LQ45, and IDXValue30.

The adoption of this two-stage approach is inspired by prior studies. For example, Abdi, Abolmakarem, Yazdi, Tan, and Choque (2024) utilized the Long Short-Term Memory (LSTM) network to predict the trend of stock prices within the FTSE 100 and then performed portfolio selection based on Sharpe Ratio maximization. Similarly, Chaweewanchon and Chaysiri (2022) proposed a portfolio formation strategy by combining the predictive capability of the Convolutional Neural Network Bidirectional Long Short-Term Memory (CNN-BiLSTM) model with the Markowitz weighting strategy on the SET50 index. Both studies emphasize the superiority of the proposed strategy; however, they primarily applied the framework to stable, well-established indices, leaving a clear research gap for emerging markets such as Indonesia.

In addition to the two-stage approach, Shapley Additive Explanations (SHAP) are applied at the end of the modeling phase to improve the transparency and interpretability of the resulting predictions. SHAP provides detailed breakdowns regarding how each input variable affects the model's predictions, thereby enabling informed interpretation of the results and allowing for hypothesis validation of the technical and macroeconomic indicators.

3.2. Data Samples and Variables

This study utilizes daily historical data from January 2022 to December 2024 for machine learning-based stock price prediction and portfolio construction. This period is deliberately chosen to exclude the COVID-19 pandemic years, as they represent force majeure events. Including such periods could introduce abnormal market conditions, making it difficult for machine learning models to effectively identify consistent patterns between variables.

The dataset comprises historical stock information, technical indicators, and macroeconomic variables. The data are then divided into a training set (January 2022 – September 2024) and a testing set (October 2024 – December 2024). The training set is used to develop and fine-tune the machine learning models, while the testing set is reserved for out-of-sample evaluation to assess predictive performance.

A total of 33 Indonesian firms have been selected as the sample for this study. These stocks are primarily large-cap, dividend-paying companies with extensive financial data availability. They are also well-distributed across sectors, ensuring a balanced representation of the Indonesian market. The number of firms was determined to be optimal, given the scope of the study. Table 1 provides a list of the selected stocks.

The variables were then categorized into two groups: independent and dependent variables. The dependent variable in this study is the three-month-ahead closing price of each stock. This prediction target is selected for its relevance to medium-term investment strategies, which are common among both institutional and retail investors. A three-month horizon is adequate to capture various factors and signals, including earnings cycles, macroeconomic developments, and firm-specific events. It also aligns with investors' expectations to balance risk and reward within a realistic timeframe, such as aiming for a 5% return over a quarter.

Table 1. List of selected stocks for this study.

No.	Stock	No.	Stock	No.	Stock
1	ADRO.JK	12	BYAN.JK	23	MTEL.JK
2	AMRT.JK	13	CMRY.JK	24	MYOR.JK
3	ASII.JK	14	CPIN.JK	25	NCKL.JK
4	BBCA.JK	15	HMSP.JK	26	PANI.JK
5	BBNI.JK	16	ICBP.JK	27	PNBN.JK
6	BBRI.JK	17	INDF.JK	28	SILO.JK
7	BMRI.JK	18	ISAT.JK	29	TBIG.JK
8	BNGA.JK	19	KLBF.JK	30	TLKM.JK
9	BREN.JK	20	MASA.JK	31	TPIA.JK
10	BRIS.JK	21	MEGA.JK	32	UNTR.JK
11	BRPT.JK	22	MSIN.JK	33	UNVR.JK

On the other hand, the independent variables include each stock's historical closing, high, low, open, and volume data. Additionally, three technical indicators are derived from the historical closing prices: the three-month EMA, the RSI, and the MACD. Furthermore, several macroeconomic indicators are also incorporated, including the USDIDR, the DJI, HSI, Nikkei 225, FTSE, and SUN. These variables are selected based on their proven reliability in financial forecasting due to their ability to capture both domestic and global market dynamics that may influence Indonesian stock price movements, as previously detailed in the Literature Review section.

3.3. Machine Learning Models

Three machine learning models are utilized in this study, namely the Random Forest (RF), Support Vector Regression (SVR), and a hybrid ensemble model constructed using the Bootstrap Aggregating (Bagging) method. These models are selected based on their strong performance in financial modeling, along with their ability to effectively model complex nonlinear relationships within a dataset.

Random Forest employs an ensemble learning framework, where it models a predetermined number of decision trees and then outputs their average prediction. This framework enhances generalizability, making RF particularly robust against overfitting. Previous studies have highlighted RF's strong performance in the context of stock price forecasting. For example, Meher, Singh, Birau, and Anand (2024) demonstrated that RF can effectively handle high-frequency trading data, further supported by Omar, Huang, Salameh, Khurram, and Fareed (2022) who found that RF can outperform even DL models when data samples are limited. Yin, Li, Li, and Zhang (2023) also found that RF excels in capturing medium and long-term trends across U.S. stocks.

Support Vector Regression (SVR) is a variation of the Support Vector Machine (SVM) algorithm, specifically designed to handle regression tasks. SVR maps input features into high-dimensional spaces through the use of kernel functions, enabling it to model both linear and nonlinear patterns. This makes SVR particularly adept at modeling stock price data, as highlighted by previous research such as those conducted by Dash, Nguyen, Cengiz, and Sharma (2023) and Thumu and Nellore (2024), where they demonstrated that tuned SVR models outperformed conventional methods in stock price forecasting. Furthermore, Huang, Deng, Zhang, and Bao (2022) also found superior predictive accuracy from SVR models integrated with empirical mode decomposition compared to benchmark models.

Bagging method is also applied with the aim of enhancing predictive performance. The Bagging framework trains multiple RF and SVR models in parallel, then aggregates their predictions by averaging. This framework aims to further reduce variance and improve the stability of the models. After the initial modeling process is completed, feature-selected versions of each model are developed, abbreviated as RFSel, SVRSel, and BaggingSel. The results will be compared to explore the effect of feature selection on forecasting accuracy.

In this study, Shapley Additive Explanations (SHAP), an explainable AI technique derived from cooperative game theory, was integrated to enhance model interpretability. Each variable in the prediction model has an impact, and SHAP helps explain the value of each feature by providing a contribution measurement. Such features are instrumental in financial modeling to technically validate the influence of various parameters, both macroeconomic and subtler in nature, supporting hypothesis validation and drawing managerially relevant conclusions.

3.4. Portfolio Construction

A critical aspect of portfolio creation involves asset weight allocation, which directly affects the portfolio's risk and return profile. Over time, various approaches to portfolio weighting have developed, ranging from classical methods like Markowitz's mean-variance optimization to modern techniques employing heuristic algorithms. For example, Wu, Wang, and Wu (2022) compared four portfolio weighting methods: equal weighting, inverse volatility, risk parity, and Sharpe Ratio-optimized Markowitz model. They found that the Markowitz model produced the highest annual return. However, Malladi and Fabozzi (2017) provided both theoretical and empirical evidence that equal weighting outperforms value-weighted methods, a view also supported by Swade, Nolte, Shackleton, and Lohre (2023).

According to the findings above, the present study applies three conventional portfolio weighting techniques: Equal Weighting, Inverse Volatility Weighting, and the Markowitz model. Besides these, a novel weighting approach is proposed, referred to as Inverse MAPE Weighting, which assigns larger weights to stocks whose predictive models had smaller forecasting errors, quantified by the Mean Absolute Percentage Error (MAPE) of the model during its evaluation phase.

4. RESULTS AND DISCUSSION

4.1. Machine Learning Model Performance

To assess the predictive accuracy of the machine learning models, three evaluation metrics were employed: the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE), and the Mean Absolute Percentage Error (MAPE). The best-performing model for each stock, along with its corresponding MAE, RMSE, and MAPE values on the test set, is summarized in Table 2.

Table 2. Machine learning model evaluation results.

Stocks	Best model	Test MAE	Test RMSE	Test MAPE (%)
ADRO.JK	SVRSel	289.222	356.181	11.659
AMRT.JK	SVR	158.303	212.882	4.876
ASII.JK	SVRSel	209.566	254.574	4.089
BBCA.JK	RF	220.748	266.801	2.138
BBNI.JK	Bagging	168.301	204.021	3.359
BBRI.JK	SVR	267.444	321.522	6.219
BMRI.JK	Bagging	384.034	468.377	6.047
BNGA.JK	Bagging	48.217	57.140	2.674
BREN.JK	RF	1914.267	2226.854	27.884
BRIS.JK	SVR	254.377	292.381	8.763
BRPT.JK	SVR	108.412	127.526	11.728
BYAN.JK	SVRSel	1494.414	1709.630	7.997
CMRY.JK	RF	151.707	187.884	2.840
CPIN.JK	BaggingSel	164.427	201.845	3.388
HMSP.JK	RF	67.090	77.214	10.138
ICBP.JK	SVRSel	1084.231	1212.735	8.886
INDF.JK	RFSel	1225.323	1348.956	15.855
ISAT.JK	RF	241.769	276.860	10.206
KLBF.JK	RFSel	74.423	105.315	4.952
MASA.JK	RFSel	269.685	335.842	4.350
MEGA.JK	SVR	233.335	306.853	5.068
MSIN.JK	Bagging	93.967	111.263	8.300
MTEL.JK	SVR	27.190	32.670	4.409
MYOR.JK	RF	137.967	159.200	5.082
NCKL.JK	SVR	70.247	91.929	8.671

Stocks	Best model	Test MAE	Test RMSE	Test MAPE (%)
PANI.JK	RF	8370.740	8866.462	54.250
PNBN.JK	Bagging	459.381	490.360	24.497
SILO.JK	RFSel	78.767	121.349	2.556
TBIG.JK	SVRSel	31.428	41.933	1.624
TLKM.JK	SVRSel	189.913	221.010	6.984
TPIA.JK	SVRSel	838.046	955.837	10.317
UNTR.JK	BaggingSel	2160.953	2616.879	7.980
UNVR.JK	SVR	472.190	549.183	25.816
Average MAPE (%)				9.806

While MAE and RMSE quantify prediction errors in absolute terms and are sensitive to the data's scale, MAPE expresses the error as a percentage, offering a scale-independent and more interpretable metric for cross-stock comparison. Notably, the MAPE values are generally below 20%, with a substantial number of stocks achieving MAPE scores under 10%. The average MAPE across the stocks is 9.806%, with the best-performing model observed for TBIG.JK at a MAPE of 1.624%. These results indicate strong forecasting performance across the selected models. This high level of accuracy supports the study's initial hypothesis and addresses the research gap identified in the introduction, demonstrating that the integration of macroeconomic indicators into machine learning models can significantly enhance stock price prediction.

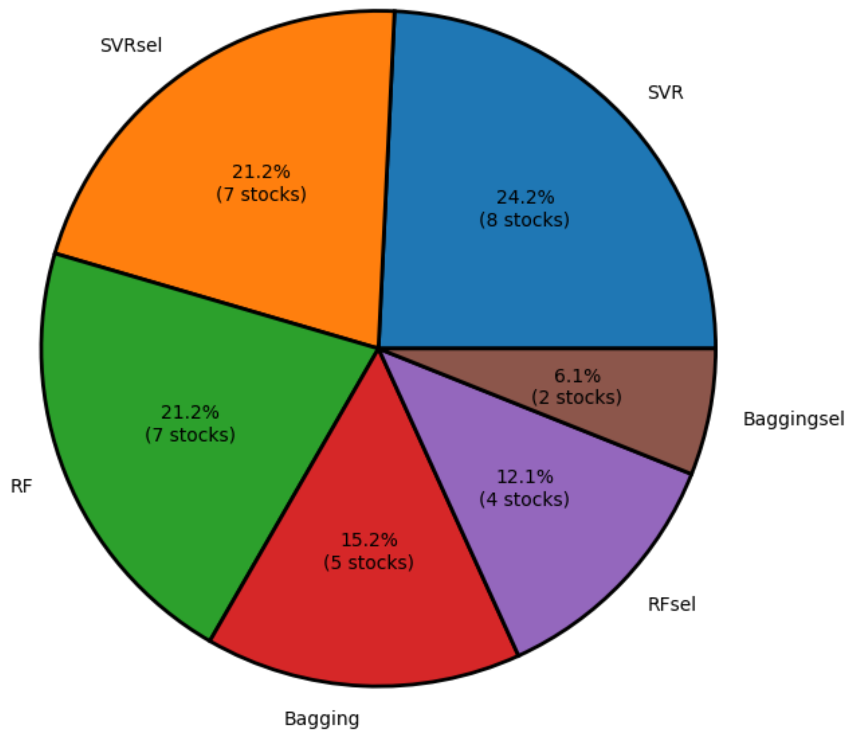

Figure 1. Recap of the selected models.

Figure 1 presents the frequency with which each machine-learning model was selected as the best-performing model across 30 stocks. SVR emerges as the most frequently chosen, with 15 stocks selecting it as their optimal model, specifically 8 using SVR and 7 using SVRSel. This is followed by RF, which was chosen for 11 stocks (7 RF and 4 RFSel), while Bagging was the least frequently selected, accounting for just 7 stocks in total (5 Bagging and 2 BaggingSel). An additional observation is that models using the full set of features consistently outperformed their feature-selected counterparts. This implies that retaining a broader range of input variables provides more contextual information, possibly capturing important interactions that enhance predictive accuracy.

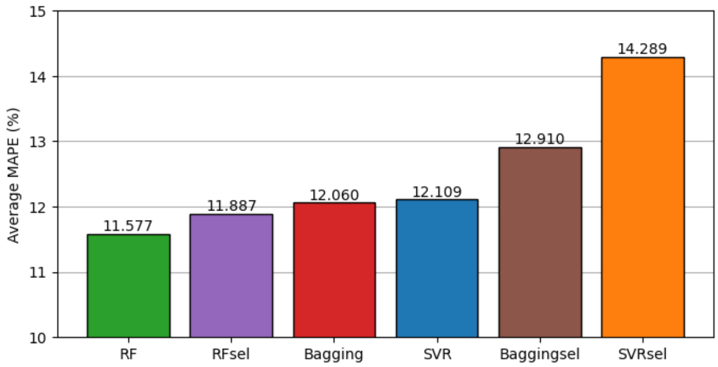

Figure 2. Average MAPE of the models.

To complement the model selection analysis, Figure 2 reports the average MAPE of each model across all stocks. Interestingly, while SVR-based models were most often selected as the best model, the RF variants demonstrated the most consistent accuracy overall. The RF and RFSel models recorded the lowest average MAPE scores of 11.577% and 11.887%, respectively. This indicates that although SVR may deliver exceptional results under specific configurations, Random Forest tends to offer more reliable performance across a broader set of stocks. Conversely, Bagging models consistently yielded the highest error rates, suggesting that their added complexity may lead to overfitting and diminished generalization.

4.2. Constructed Portfolio Performance

Following the identification of the best-performing model and its optimal hyperparameters for each stock, forecasts were generated for stock closing prices on March 27, 2025, the final trading day of Q1 2025. These forecasts were used to estimate expected returns and compute the Sharpe Ratios. Only three stocks recorded Sharpe Ratios exceeding 1, namely BMRI.JK, BBNI.JK, and MEGA.JK, and were thus selected for portfolio construction. Four weighting strategies were applied: Equal Weight (ML-EW), Inverse Volatility (ML-IV), Mean-Variance (ML-MV), and Inverse MAPE (ML-MAPE). Portfolio performance was then evaluated based on realized returns and volatility during the Q1 2025 period using historical daily data.

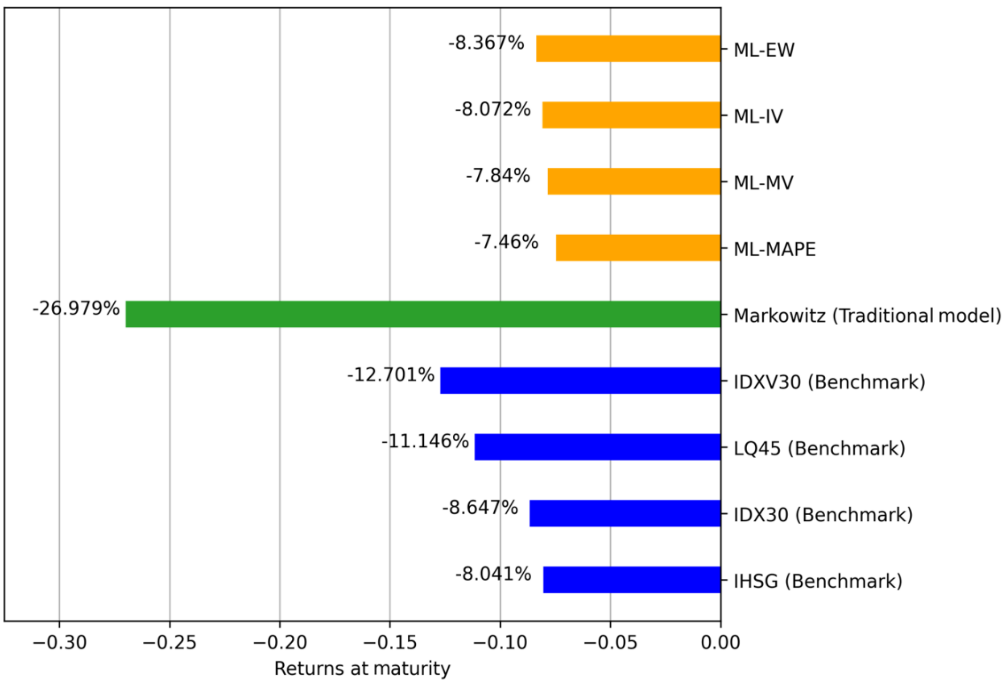

Figure 3. Returns-at-maturity of portfolios and benchmarks.

Figure 3 presents the returns at maturity, specifically on March 27th, 2025, for the ML integrated portfolios, alongside the traditional Markowitz portfolio and the Indonesian market benchmarks. Although all portfolios and benchmarks posted negative returns attributable to a market-wide downturn, the ML-integrated portfolios consistently outperformed the traditional Markowitz portfolio. This supports Hypothesis 1 (H_1), confirming that ML-based strategies can yield superior returns relative to traditional methods even in adverse market conditions. Furthermore, ML portfolios outperformed major Indonesian benchmarks (IDXV30, LQ45, IDX30), with ML-MV and ML-MAPE even surpassing IHSG, thereby validating Hypothesis 11 (H_{11}).

Figure 4. Daily returns of portfolios and benchmarks during the Q1 2025 period.

Figure 4 shows the daily return dynamics of the portfolios. The ML-integrated portfolios, particularly the ML-MV portfolio, achieved the highest gains on select days but also experienced greater volatility, indicating a higher-risk, higher-reward profile. In contrast, the benchmark indexes showed more stable and moderate returns, characteristic of strategies aimed at capital preservation. The traditional Markowitz portfolio, although grounded in established theory, displayed erratic performance and higher volatility, highlighting its limitations in capturing recent market patterns.

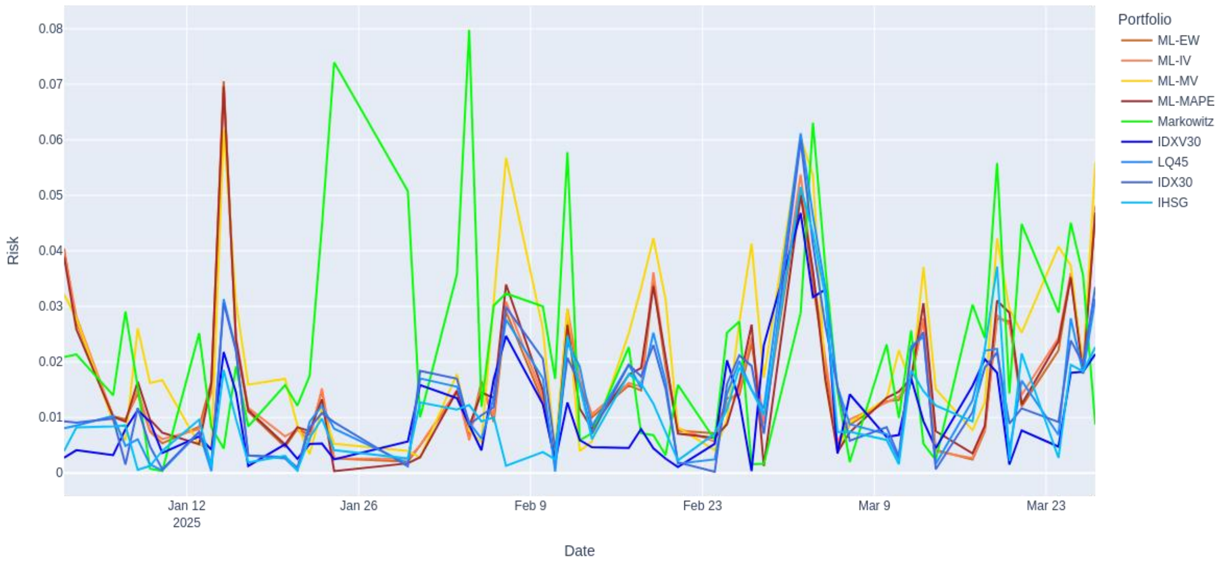

Figure 5. Daily risks of portfolios and benchmarks during the Q1 2025 period.

Figure 5 illustrates the daily risk trajectories of the constructed portfolios compared to the benchmark indexes. Machine learning portfolios generally exhibited higher risk than the benchmarks, with the ML-MV portfolio showing the most volatility. Nevertheless, there were periods when some machine learning portfolios had lower risk levels than the indexes, indicating their adaptive potential. The traditional Markowitz portfolio exhibited the most erratic risk profile, further supporting the case for machine learning-driven approaches in dynamic market environments. These patterns suggest that while benchmark indexes cater to conservative investors, machine learning-based portfolios may appeal to those seeking higher returns and willing to accept greater risk.

4.3. SHAP-Based Feature Interpretation

To examine how input variables influence the model's predictions, SHAP (Shapley Additive Explanations) is employed to provide interpretable insights. Figure 6 presents the SHAP summary plot, which visualizes the aggregated impact of features from the best-performing models. In this plot, each dot represents a single observation in the dataset. The vertical axis lists the input features in descending order of importance, from the most to the least influential. The horizontal axis reflects each feature's contribution to the model's prediction, shifting predictions either higher (right) or lower (left). The colour gradient indicates the value of the feature for each observation, with red representing high values and blue indicating low values.

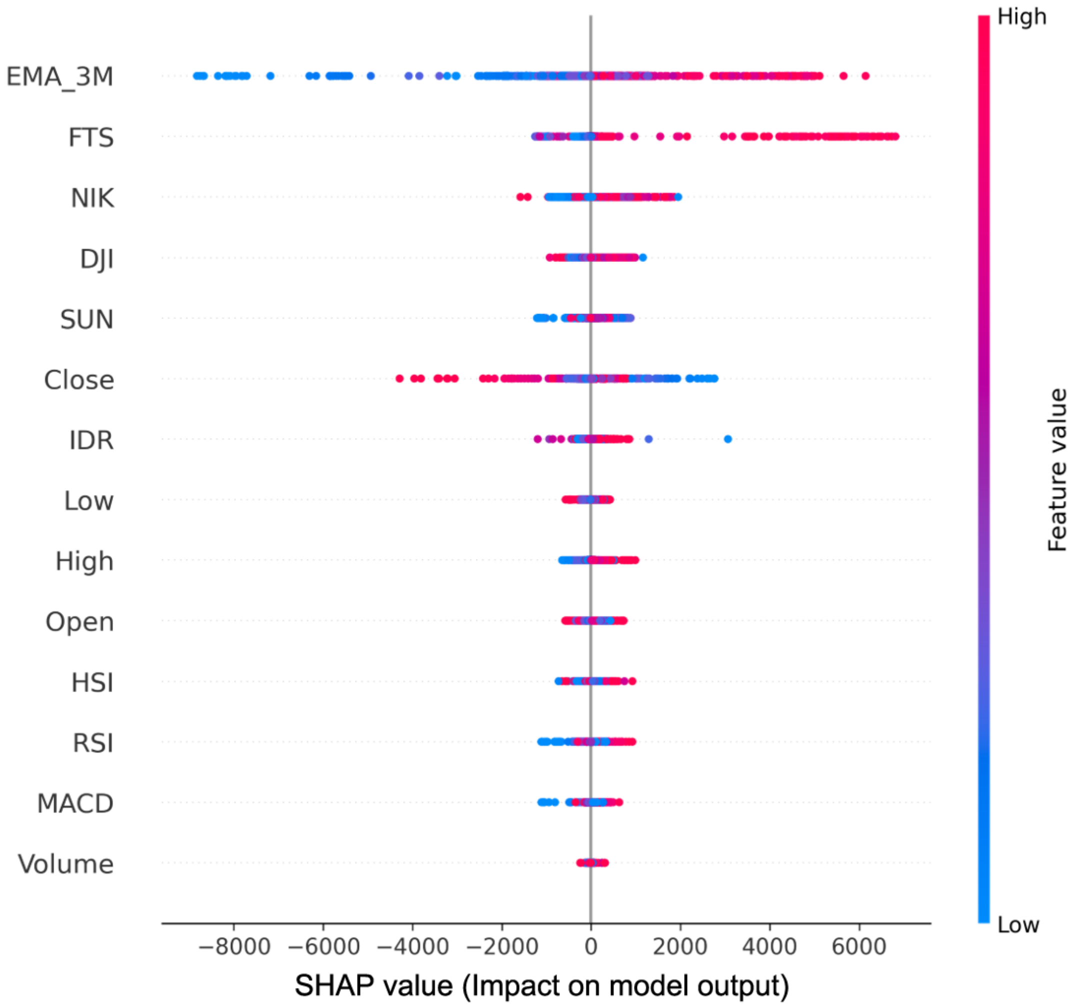

Figure 6. SHAP summary plot.

The SHAP analysis reveals that the 3-month EMA is the most influential variable in the models' predictions, indicating that a stock's recent price trend is the strongest determinant of its price movement over the next three months. Conversely, trading volume is the least predictive feature identified in the analysis, suggesting that the number of shares traded has minimal impact on long-term stock price direction. This result is consistent with earlier studies that also found the limited contribution of trading volume to forecasting long-term stock prices (Bajzik, 2021).

Notably, the FTS, NIK, DJI, and SUN emerge as four of the five most impactful features, underscoring the significance of macroeconomic indicators in shaping the model predictions. This highlights the importance of global economic dynamics and sentiment in influencing local stock price movements. On the other hand, the RSI and MACD indicators rank among the top three least influential variables, indicating that most technical indicators, with the exception of the 3-month EMA, exhibit little influence on the model predictions. This finding aligns well with the widely accepted view that technical indicators are preferred for short-term trading and, therefore, are limited in their ability to forecast long-term movements, such as the three-month time frame in this study.

Notably, the FTS, NIK, DJI, and SUN emerge as four of the five most impactful features, underscoring the significance of macroeconomic indicators in shaping the model's predictions. This highlights the importance of global economic dynamics and sentiment in influencing local stock price movements (Omar, Ali, Mouneer, Kouser, & Al-Faryan, 2022). On the other hand, the RSI and MACD indicators rank among the top three least influential variables, indicating that most technical indicators, with the exception of the 3-month EMA, exhibit little influence on the model's predictions. This finding aligns well with the widely accepted view that technical indicators are preferred for short-term trading and are therefore limited in their ability to forecast long-term movements, such as the three-month time frame used in this study.

Regarding the relationship between technical indicators and future stock prices, a clear positive relationship is observed between the 3-month EMA and the predicted 3-month-ahead closing prices. Low EMA values consistently lead to lower predicted prices, while high EMA values correspond with higher predictions. This consistent pattern supports H_2. In contrast, the patterns for RSI and MACD are less straightforward. While higher values of these indicators often align with increased predictions and lower values with decreased ones, several outliers disrupt this trend. These inconsistencies suggest a complex, nonlinear relationship. As a result, H_3 and H_4, which assume a linear association, are not supported. Similar nonlinear patterns could be observed in macroeconomic indicators, including USDIDR, DJI, HSI, NIK, and SUN. Once again, the inconsistencies indicate that these variables do not have a consistent linear relationship with future stock prices; thus, H_5 through H_8 and H_{10} are not proven. However, the FTS index does exhibit a linear pattern, where low to moderate values are associated with lower predictions, while higher values are associated with increased predictions. This supports H_9, which states that there exists a positive linear relationship between FTS and future stock prices.

4.4. Discussion

This study aims to assess the effectiveness of machine learning (ML) models in forecasting stock prices and constructing portfolios in the Indonesian capital market, with a focus on the integration of macroeconomic and technical indicators into the models. Moreover, this study also seeks to analyze the extent of influence that these indicators have on the model predictions. Several important insights could be gained from the findings.

First, the robust predictive capability of ML models based on macroeconomic indicators underscores the dominance of international market determinants in affecting domestic stock volatility. This illustrates the overwhelming impact of trends in international markets and overall economic conditions in determining the valuation of individual firms. The results documented are in line with the existing body of literature showing the impact of macroeconomic variables on stock market performance (Hashmi & Chang, 2023; Khan et al., 2023; Prasad et al., 2022); hence, emphasizing the need for their inclusion in forecasting models, particularly in emerging markets.

Second, the performance demonstrated by ML-integrated portfolios, particularly regarding maturity returns, indicates their real-world capabilities in comparison to benchmark methods, such as conventional portfolio optimization techniques and Indonesian market benchmarks. The findings confirm hypotheses H_1 and H_{11}, which stated that ML-integrated portfolios would perform better than the Markowitz model and local market benchmarks. The reported findings are consistent with previous research that justifies the application of machine learning techniques in portfolio construction (Aithal, Geetha, Dinesh, Savitha, & Menon, 2023; Alzaman, 2024; Padhi, Padhy, Bhoi, Shafi, & Yesuf, 2022). Nevertheless, given that the research in this study utilized descriptive performance measures instead of rigorous statistical testing, the findings must be interpreted as suggestive and not absolutely conclusive from a statistical perspective. In addition, analysis of daily returns trajectories shows that while ML-based portfolios occasionally outperform benchmarks, benchmarks are more consistent in their risk management and, therefore, may be more appropriately positioned for risk-averse investors.

Third, SHAP model interpretability was helpful in identifying the drivers of model prediction. The 3-month EMA was identified as the most influential variable, suggesting that the recent price trend of a stock is a very good predictor of the medium-term future price of the stock, thus confirming H_2. In contrast, other technical indicators such as the RSI and MACD exhibited complex, nonlinear patterns. These findings do not support H_3 and H_4 and suggest that while such indicators may be useful for short-term trading strategies, they have limited reliability in longer-term forecasting. This conclusion is supported by prior research showing that technical indicators may underperform in long-horizon prediction tasks (Dai, Dong, Kang, & Hong, 2020).

Finally, results related to macroeconomic variables were mixed. The FTS demonstrated a clear, linear positive relationship with stock price predictions, confirming H_9. However, other macroeconomic indicators, such as USDIDR, DJI, HIS, NIK, and SUN, exhibited nonlinear influences and, therefore, did not support H_5 through H_8 and H_{10}. Nevertheless, when assessed by overall feature importance, macroeconomic indicators showed a stronger influence on model predictions than most technical indicators. This finding is consistent with Latif et al. (2023), who also observed that macroeconomic variables contributed more significantly to prediction accuracy than technical indicators when interpreted through SHAP analysis.

These findings reinforce the value of integrating macroeconomic context with machine learning to enhance stock price forecasting. They also highlight the importance of interpretable models in capturing nonlinear market dynamics. Although not statistically validated, the observed performance of ML-integrated portfolios, particularly under volatile conditions, suggests their potential as adaptive, data-driven alternatives to traditional strategies. This study contributes to the growing application of AI in investment decision-making, emphasizing the balance between predictive accuracy and practical portfolio outcomes.

5. CONCLUSIONS AND RECOMMENDATIONS

This study examined the use of machine learning models in forecasting stock prices and constructing portfolios, with a particular focus on integrating macroeconomic and technical indicators. The results show that integrating macroeconomic variables successfully contributes to a robust and accurate long-term stock price predictive model, achieving an average MAPE of 0.098. Analysis using SHAP reveals that macroeconomic variables have a greater influence on predictive performance than most technical indicators. However, the 3-month EMA stands out not only as the most impactful technical feature but also in relation to all input variables. Machine learning–integrated portfolios, especially those optimized using mean-variance and inverse MAPE weighting, achieved higher returns at maturity compared to traditional and benchmark strategies.

These findings present both theoretical and practical contributions. Theoretically, they advance the literature on stock market prediction by emphasizing the role of macroeconomic indicators in emerging markets. Furthermore, this study applies a machine learning-integrated method for portfolio construction, revealing the benefits and disadvantages of such methods in the Indonesian capital market. Practically, the findings offer value not only for individual investors but also for fund managers and policymakers interested in incorporating global market signals into decision-making. For investors, it highlights the potential of data-driven, adaptive portfolio construction to enhance performance in dynamic market conditions. At the policy level, financial regulators and institutions in emerging markets like Indonesia should improve financial infrastructure, encourage transparency in macroeconomic reporting, and promote investor education programs to support the responsible use of machine learning in portfolio management. Such policies could help align local investment practices with global trends.

However, the study is not without its limitations. First, this research is limited to a single market and a three-month forecasting horizon. Second, the predictive models in this study do not utilize the time series nature of the data. Future research could explore broader timeframes, cross-market comparisons, additional model explainability tools, and integrate the time series nature of the data along with macroeconomic indicators to further strengthen the applicability of machine learning in financial strategy.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

Abdi, F., Abolmakarem, S., Yazdi, A. K., Tan, Y., & Choque, I. A. M. (2024). Prospective portfolio optimization with asset preselection using a combination of long and short term memory and Sharpe ratio maximization. *IEEE Access, 12*, 144280–144294. https://doi.org/10.1109/ACCESS.2024.3466829

Aithal, P. K., Geetha, M., Dinesh, U., Savitha, B., & Menon, P. (2023). Real-time portfolio management system utilizing machine learning techniques. *IEEE Access, 11*, 32595-32608. https://doi.org/10.1109/ACCESS.2023.3263260

Albahli, S., Irtaza, A., Nazir, T., Mehmood, A., Alkhalifah, A., & Albattah, W. (2022). A machine learning method for prediction of stock market using real-time twitter data. *Electronics, 11*(20), 3414. https://doi.org/10.3390/electronics11203414

Almaafi, A., Bajaba, S., & Alnori, F. (2023). Stock price prediction using ARIMA versus XGBoost models: The case of the largest telecommunication company in the Middle East. *International Journal of Information Technology, 15*(4), 1813-1818. https://doi.org/10.1007/s41870-023-01260-4

Alzaman, C. (2024). Deep learning in stock portfolio selection and predictions. *Expert Systems with Applications, 237*, 121404. https://doi.org/10.1016/j.eswa.2023.121404

Annaufal, A. I., Mariyana, A. L. D., & Roostika, R. (2024). The role of artificial intelligence in stock forecasting in Indonesian Stock Exchange firm. In Digital Technology and Changing Roles in Managerial and Financial Accounting: Theoretical Knowledge and Practical Application. In (pp. 27–35). Leeds: Emerald Publishing. https://doi.org/10.1108/S1479-351220240000036003

Assagaf, A., Murwaningsari, E., Gunawan, J., & Mayangsari, S. (2019). The effect of Macro economic variables on stock return of companies that listed in stock exchange: Empirical evidence from Indonesia. *International Journal of Business and Management, 14*(8), 108-116. https://doi.org/10.5539/ijbm.v14n8p108

Bagalkot, S. S., Dinesha, H. A., & Naik, N. (2024). Novel grey wolf optimizer based parameters selection for GARCH and ARIMA models for stock price prediction. *PeerJ Computer Science, 10*, e1735. https://doi.org/10.7717/peerj-cs.1735

Bajzik, J. (2021). Trading volume and stock returns: A meta-analysis. *International Review of Financial Analysis, 78*, 101923. https://doi.org/10.1016/j.irfa.2021.101923

Berger, T., & Koubová, J. (2024). Forecasting Bitcoin returns: Econometric time series analysis vs. machine learning. *Journal of Forecasting, 43*(7), 2904-2916. https://doi.org/10.1002/for.3165

Chang, Y.-H., & Huang, C.-W. (2024). Utilizing genetic algorithms in conjunction with ANN-based stock valuation models to enhance the optimization of stock investment decisions. *AI, 5*(3), 1011-1029. https://doi.org/10.3390/ai5030050

Chaweewanchon, A., & Chaysiri, R. (2022). Markowitz mean-variance portfolio optimization with predictive stock selection using machine learning. *International Journal of Financial Studies, 10*(3), 64. https://doi.org/10.3390/ijfs10030064

Dai, Z., Dong, X., Kang, J., & Hong, L. (2020). Forecasting stock market returns: New technical indicators and two-step economic constraint method. *The North American Journal of Economics and Finance*, *53*, 101216. https://doi.org/10.1016/j.najef.2020.101216

Dash, R. K., Nguyen, T. N., Cengiz, K., & Sharma, A. (2023). Fine-tuned support vector regression model for stock predictions. *Neural Computing and Applications*, *35*(32), 23295-23309. https://doi.org/10.1007/s00521-021-05842-w

Du, S., & Shen, H. (2024). Reinforcement learning-based multimodal model for the stock investment portfolio management task. *Electronics*, *13*(19), 3895. https://doi.org/10.3390/electronics13193895

Gulko, L. (2002). Decoupling. *The Journal of Portfolio Management*, *28*(3), 59-66. https://doi.org/10.3905/jpm.2002.319843

Hashmi, S. M., & Chang, B. H. (2023). Asymmetric effect of macroeconomic variables on the emerging stock indices: A quantile ARDL approach. *International Journal of Finance & Economics*, *28*(1), 1006-1024. https://doi.org/10.1002/ijfe.2461

Huang, Y., Deng, C., Zhang, X., & Bao, Y. (2022). Forecasting of stock price index using support vector regression with multivariate empirical mode decomposition. *Journal of Systems and Information Technology*, *24*(2), 75-95. https://doi.org/10.1108/JSIT-12-2019-0262

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Khan, M. K., Teng, J. Z., Khan, M. I., & Khan, M. F. (2023). Stock market reaction to macroeconomic variables: An assessment with dynamic autoregressive distributed lag simulations. *International Journal of Finance & Economics*, *28*(3), 2436-2448. https://doi.org/10.1002/ijfe.2543

Kheimi, M., Almadani, M., & Zounemat-Kermani, M. (2024). Stochastic (S [ARIMA]), shallow (NARnet, NAR-GMDH, OS-ELM), and deep learning (LSTM, Stacked-LSTM, CNN-GRU) models, application to river flow forecasting. *Acta Geophysica*, *72*(4), 2679-2693. https://doi.org/10.1007/s11600-023-01157-7

Kumbure, M. M., Lohrmann, C., Luukka, P., & Porras, J. (2022). Machine learning techniques and data for stock market forecasting: A literature review. *Expert Systems with Applications*, *197*, 116659. https://doi.org/10.1016/j.eswa.2022.116659

Laichena, K. E., & Obwogi, T. N. (2015). Effects of macroeconomic variables on stock returns in the East African community stock exchange market. *International Journal of Education and Research*, *3*(10), 305-320.

Latif, N., Selvam, J. D., Kapse, M., Sharma, V., & Mahajan, V. (2023). Comparative performance of LSTM and ARIMA for the short-term prediction of bitcoin prices. *Australasian Accounting, Business and Finance Journal*, *17*(1), 256–276. https://doi.org/10.14453/aabfj.v17i1.15

López De Prado, M., Simonian, J., Fabozzi, F. A., & Fabozzi, F. J. (2025). Enhancing Markowitz's portfolio selection paradigm with machine learning. *Annals of Operations Research*, *346*, 319–340. https://doi.org/10.1007/s10479-024-06257-1

Malladi, R., & Fabozzi, F. J. (2017). Equal-weighted strategy: Why it outperforms value-weighted strategies? Theory and evidence. *Journal of Asset Management*, *18*, 188-208. https://doi.org/10.1057/s41260-016-0033-4

Manurung, A. H., Sinaga, N. Y., & Manurung, A. (2023). Construction portfolio using elton gruber model: COVID-19. *Journal of Applied Finance & Banking*, *13*(4), 111-122. https://doi.org/10.47260/jafb/1346

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.2307/2975974

Meher, B. K., Singh, M., Birau, R., & Anand, A. (2024). Forecasting stock prices of fintech companies of India using random forest with high-frequency data. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1), 100180. https://doi.org/10.1016/j.joitmc.2023.100180

Mie, M. (2014). Analysis of the influence of foreign composite stock price index on the Indonesian composite stock price index. *Jurnal Wira Ekonomi Mikroskil*, *4*(2), 81-90.

Migliavacca, M., Goodell, J. W., & Paltrinieri, A. (2023). A bibliometric review of portfolio diversification literature. *International Review of Financial Analysis*, *90*, 102836. https://doi.org/10.1016/j.irfa.2023.102836

Nasution, M. R., Rujiman, R., & Tanjung, A. A. (2023). Analysis of the effect of world crude oil prices, exchange rates, inflation, Dow Jones industrial average, and the Nikkei 225 Index on the composite stock price index. *Quantitative Economics and Management Studies*, *4*(4), 764-772.

Omar, A. B., Ali, A., Mouneer, S., Kouser, R., & Al-Faryan, M. A. S. (2022). Is stock market development sensitive to macroeconomic indicators? A fresh evidence using ARDL bounds testing approach. *Plos one*, *17*(10), e0275708. https://doi.org/10.1371/journal.pone.0275708

Omar, A. B., Huang, S., Salameh, A. A., Khurram, H., & Fareed, M. (2022). Stock market forecasting using the random forest and deep neural network models before and during the COVID-19 period. *Frontiers in Environmental Science*, *10*, 917047. https://doi.org/10.3389/fenvs.2022.917047

Padhi, D. K., Padhy, N., Bhoi, A. K., Shafi, J., & Yesuf, S. H. (2022). An intelligent fusion model with portfolio selection and machine learning for stock market prediction. *Computational Intelligence and Neuroscience*, *2022*(1), 7588303. https://doi.org/10.1155/2022/7588303

Pinelis, M., & Ruppert, D. (2022). Machine learning portfolio allocation. *The Journal of Finance and Data Science*, *8*, 35-54. https://doi.org/10.1016/j.jfds.2021.12.001

Prasad, A., Bakhshi, P., & Seetharaman, A. (2022). The impact of the US macroeconomic variables on the CBOE VIX Index. *Journal of Risk and Financial Management*, *15*(3), 126. https://doi.org/10.3390/jrfm15030126

Rachmawati., & Fadila, A. (2024). Dynamics of Idxenergy stock returns: A comprehensive analysis of GDP, exchange rates, DJIA index and oil prices. *Formosa Journal of Sustainable Research*, *3*(2), 213–230. https://doi.org/10.55927/fjsr.v3i2.8058

Raju, R. (2024). Timing the tide: The impact of rebalancing periods in momentum investing in Indian equities. *Available at SSRN 4687044*. https://doi.org/10.2139/ssrn.4687044

Rosanti, A. (2021). Determinant of Indonesian government bond yields with 1, 5 and 10 years term. *International Journal of Innovative Science and Research Technology*, *6*(1), 1087-1095.

Saleh Ahmar, A., Singh, P. K., Van Thanh, N., Viet Tinh, N., & Minh Hieu, V. (2022). Prediction of BRIC stock price using ARIMA, SutteARIMA, and Holt–Winters. *Computers, Materials & Continua*, *70*(1), 523–534. https://doi.org/10.32604/cmc.2022.017068

Santosa, P. W., & Sihombing, P. (2015). Factors affecting the yeld curve fluctuation of Indonesia government bond. *International Journal of Applied Business and Economic Research*, *13*(6), 4073-4087.

Santoso, K., Tannia, T., Siratan, E. D., Renaganis, A. E., Jessie, J., & Handoko, H. (2023). The effect of the global stock exchange index on the Indonesia Composite Index (ICI) in the Indonesia stock exchange for 2016-2021 period. *Jurnal Muara Ilmu Ekonomi Dan Bisnis*, *7*(1), 126-139. https://doi.org/10.24912/jmieb.v7i1.22807

Shah, J., Vaidya, D., & Shah, M. (2022). A comprehensive review on multiple hybrid deep learning approaches for stock prediction. *Intelligent Systems with Applications*, *16*, 200111. https://doi.org/10.1016/j.iswa.2022.200111

Sihombing, P., Siregar, H., Manurung, A. H., & Santosa, P. W. (2014). Determinants of the Indonesia government yield curve. *International Journal of Information Technology and Business Management*, *25*(1), 22-35.

Sonkavde, G., Dharrao, D. S., Bongale, A. M., Deokate, S. T., Doreswamy, D., & Bhat, S. K. (2023). Forecasting stock market prices using machine learning and deep learning models: A systematic review, performance analysis and discussion of implications. *International Journal of Financial Studies*, *11*(3), 94. https://doi.org/10.3390/ijfs11030094

Sundoro, H. S. (2018). The influence of macroeconomic factors, liquidity factors and external factors on the yield of Indonesian government bonds. *Journal of Business & Applied Management*, *11*(1), 102-115.

Swade, A., Nolte, S., Shackleton, M. B., & Lohre, H. (2023). Why do equally weighted portfolios beat value-weighted ones? *The Journal of Portfolio Management*, *49*(5), 167–187. https://doi.org/10.3905/jpm.2023.1.482

Tanto, V. M., & Kurniawan, T. A. (2022). Development of web-based stock investment recommendation system (Case Study: Reliance Securities Malang). *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, *6*(6), 2813-2821.

Thumu, S. R., & Nellore, G. (2024). Optimized ensemble support vector regression models for predicting stock prices with multiple kernels. *Acta Informatica Pragensia*, *13*(1), 24-37. https://doi.org/10.18267/j.aip.226

Tursunbaevich, M. F. (2020). Stock market as the main segment of capital market. *International Journal of Psychosocial Rehabilitation*, *24*(5), 6669–6676.

Verkino, B., Sinaga, B. M., & Andati, T. (2020). Optimal stock investment portfolio from 6 sectors in the LQ45 index for the 2015-2018 period. *Jurnal Aplikasi Bisnis dan Manajemen, 6*(2), 389-389. https://doi.org/10.17358/jabm.6.2.389

Wu, D., Wang, X., & Wu, S. (2022). Construction of stock portfolios based on k-means clustering of continuous trend features. *Knowledge-Based Systems, 252*, 109358. https://doi.org/10.1016/j.knosys.2022.109358

Wu, W. (2023). Risk management of enterprise quantitative investment strategies through data modeling. *Journal of Engineering, Project & Production Management, 13*(1), 76-80. https://doi.org/10.32738/JEPPM-2023-0008

Yin, L., Li, B., Li, P., & Zhang, R. (2023). Research on stock trend prediction method based on optimized random forest. *CAAI Transactions on Intelligence Technology, 8*(1), 274-284. https://doi.org/10.1049/cit2.12067

Yuliarta, V., & Bebasari, N. (2023). The influence of the dow jones industrial average (DJIA), inflation, interest rate levels and world oil prices on the combined stock price index (IHSG) (case study on the Indonesian Stock Exchange for the 2018-2022 period). *Jurnal Manajemen, 13*(1), 25–39. https://doi.org/10.30656/jm.v13i2.6684

Zhou, S., & Meng, X. (2021). Are government bonds still safe havens in the context of COVID-19? *Applied Economics Letters, 30*(1), 14-18. https://doi.org/10.1080/13504851.2021.1971608