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Sustainable Stock Screening Based on Fundamental and Technical Indicators using Gaussian Naive Bayes Classifier

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Abstract

Investors increasingly require systematic methods for sustainable stock screening, particularly for ESG-focused benchmarks like Indonesia's SRI-KEHATI Index. This study addresses a gap by developing and evaluating a stock screening framework using a Gaussian Naive Bayes (GNB) classifier to integrate both fundamental and technical analysis. The model utilized quarterly data from 25 SRI-KEHATI stocks from Q1 2024 to Q2 2025, training on 11 indicators to predict future quarterly returns, classifying stocks as "Investable" (Label 1) or "Non-investable" (Label 0). The model achieved an average training accuracy of 74.4%, with an average sensitivity of 89.96% and specificity of 67.73%. Feature importance analysis revealed that technical indicators, such as Average Log Return, Average MACD, Average RSI, and key fundamental ratios, PBV and ROA, were the most influential predictors. Model predictions were evaluated through a simple equal-weighted portfolio simulation for Q3 2025. The simulation results showed the model-selected "Investable" portfolio generated a 29.9% return, substantially outperforming the IHSG Benchmark (16.6%) and the "Non-investable" portfolio (3.56%). Furthermore, the statistical significance was validated through Welch's Independent Samples T-Test, which yielded significant p-values ($p < 0.05$) across multiple periods, including a marginally significant of $p = 0.0592$ for Q3 2025. These findings demonstrate that the GNB classifier is an effective and statistically validated framework for sustainable stock screening, successfully identifying ESG-compliant stocks that also deliver superior financial returns and providing a practical tool for responsible investing in the Indonesian capital market.

Keywords: Screening; SRI-KEHATI; Portfolio Performance; Investable Stocks

1. INTRODUCTION

Investment in the capital market has become a regular part of modern society's life, almost like a necessity for preserving or increasing the value of their assets [9]. Rising inflation intensifies economic uncertainty and shapes investor beliefs, leading many individuals to adjust their investment behavior with a strong focus on equity markets [16]. Given the growing importance of stock investments and the complexity of market dynamics, a systematic approach to selecting high-quality and sustainable stocks has become increasingly essential. In Indonesia, one of the benchmarks that reflects sustainable investment perspective is the SRI-KEHATI Index [18]. As the first green index listed on the exchange, the SRI-KEHATI Index serves as an early benchmark for investment principles that emphasize environmental, social, and governance (ESG) issues in the Indonesian capital market [14]. It provides a clear reference for investors who seek to build portfolios that are both financially strong and socially responsible, underscoring the growing importance of sustainable stock screening for long-term economic and environmental goals.

Analyst and investors commonly rely on two major approaches to evaluate the quality of a stock, such as fundamental and technical analysis [20]. Fundamental analysis involves making predictions by examining a company's core condition, which is reflected in its financial statements and relevant macroeconomic factors [8]. Technical analysis makes predictions by examining historical price and volume data, operating under the assumption that a stock's market price has already absorbed all publicly available information, unlike fundamental analysis which determines intrinsic value from such inputs [7]. The combination of these two analytical perspectives provides a more comprehensive assessment of stock performance, making it an essential foundation for developing reliable and data-driven stock screening methods.

In recent years, classification techniques in machine learning have gained increasing attention as tools for enhancing the accuracy and consistency of stock screening. To correctly identifying stock market movements remains a major challenge in financial modeling due to the market's volatility, intricate interdependencies, and the wide range of factors that shape its behavior [1]. Among these methods, the Naive Bayes classifier is frequently used due to its simplicity, efficiency, and strong performance even when working with high-dimensional financial data [12]. By integrating fundamental and technical indicators into a probabilistic framework, Gaussian Naive Bayes enables a systematic and data-driven classification of stocks, providing investors with a more objective basis for identifying securities that align with sustainable and profitable investment criteria.

Several previous studies have explored methods for stock analysis and prediction, providing a foundation for this research. Studies from [4], [5], [7], [8], [17], highlights the profitability of machine learning classification to do stock screening or stock selection based on fundamental and technical indicators. While study from [2], highlight the use of incorporating Gaussian Naive Bayes as stock market prediction. Previous studies often overlooks the potential of efficient, interpretable probabilistic models for stock selection. This creates a gap in understanding how a lightweight classification approach can integrate both fundamental and technical indicators to screen sustainable stocks in the Indonesian market context. Therefore, this study aims to develop a stock screening framework using the Gaussian Naive Bayes classifier to classify SRI-KEHATI constituents based on combined fundamental and technical features. The purpose of this article is to demonstrate the effectiveness of this model in identifying sustainable and financially attractive stocks, as well as to provide a practical, data-driven tool that supports investors in making more informed and responsible investment decisions.

2. METHODOLOGY

2.1 Fundamental Indicators

Fundamental indicators are quantitative measures from a company's financial statements, namely the balance sheet, income statement, and cash flow statement to evaluate the true valuation of a share [13]. These indicators can be classified into distinct categories based on the specific aspect of the company's financial standing they are designed to measure [6].

1. Profitability Ratios: These ratios measure s company's ability to generate earnings relative to its revenue assets, equity, or other metrics. They are critical for assessing management

efficiency and operational success. Returns on Assets (ROA) and Earning per Share (EPS) are the two examples of profitability ratios. Where the higher both of those values, the better the efficiency and profitability of a stock.

2. Leverage (Solvency) Ratios: These ratios evaluate a company's financial risk by measuring the extent to which using debt financing high leverage can amplify returns but also increases the risk of insolvency. One of the ratios is Debt to Equity Ratio (DER), where a DER of 1.0 indicates that assets are financed equally by debt and equity and the higher the ratio than the industry average suggests aggressive debt financing.
3. Valuation (Market) Ratios: These ratios connect a company's stock price to a specific financial metric, providing a standardized way to compare market valuations. Price to Book Value (PBV) ratio that compares a company's current market capitalization to its net asset value. A low PBV suggests that the company is undervalued.

2.2 Technical Indicators

Technical indicators is mathematical calculation based on a stock's historical market data, primarily price and volume to interpret patterns, identify market trends, momentum measurements, and generate trading signals that could be used to aid in trade decision-making [13]. The following are the standard formula for several technical indicators from Equation (2.1) to Equation (2.10).

Indicator	Formula	
Average Price	$Avg\ Price = \frac{\sum_{i=1}^{n} Close\ Price_i}{n}$	(2.1)
Average Volume	$Avg\ Vol = \frac{\sum_{i=1}^{n} Volume_i}{n}$	(2.2)
Average Log Return	$R_i = \ln\left(\frac{P_i}{P_{i-1}}\right)$	(2.3)
	$Avg\ Ln\ Return = \frac{\sum_{i=1}^{n} R_i}{n}$	(2.4)
Beta (β)	$\beta = \frac{Cov(R_s, R_m)}{Var(R_m)}$	(2.5)
Moving Average (20)	$MA_t = \frac{\sum_{i=t-1}^{t-20} Close_i}{20}$	(2.6)
Relative Strength Index (RSI)	$RSI = 100 - \left[\frac{100}{1 + RS}\right]$	(2.7)
	$RS = \frac{Avg\ Gain\ over\ n\ period}{Avg\ Loss\ over\ n\ period}$	(2.8)
Moving Average Convergence Divergence (MACD)	$MACD\ Line = EMA(12) - EMA(26)$ $EMA(t) = (1-\alpha)EMA(t-1) + \alpha \times P_i$	(2.9)
	$Signal\ Line = EMA$ (9) of the MACD Line	(2.10)

where $Avg\ Price$ is the average stock price, $Avg\ Vol$ is the average trading volume, $Close\ Price_i$ is the closing price for period i, $Volume_i$ is the trading volume for period i, and n is the total number of periods. R_i represents the natural log return for a period, P_i (the price at time i, and P_{t-1} (the price at the previous time period $t-1$), while $Avg\ Ln\ Return$ is the average of these log returns. β (Beta) is the measure of systematic risk, derived from $Cov(R_s, R_m)$ (the covariance between the stock's returns, R_s, and the market's returns, R_m) and $Var(R_m)$ (the variance of the market's returns). MA_t is the Simple Moving Average calculated for the current time period t. RSI is the Relative Strength Index, which uses RS (Relative Strength), defined as the ratio of $Avg\ Gain$ (average gains over the period) to $Avg\ Loss$ (average losses over the period). Lastly, the $MACD\ Line$ is the difference between the 12-period $EMA(12)$ and the 26-period $EMA(26)$, and the Signal Line is the 9-period $EMA(9)$ calculated from the $MACD\ Line$.

2.3 Standardization Scaling

Standardization is a fundamental data preprocessing technique used in statistical analysis and machine learning to make features with different scales and units comparable. Z-Score Scaling is a linear transformation that centers features at zero mean and scales them to unit variance, resulting in a standard normal distribution without altering the original distribution's shape [11]. The formula to calculate Z-Score for a variable from a sample can be seen in Equation (2.11) also the formula of the sample average and sample standard deviation of the variable can be seen simultaneously in Equation (2.12) and Equation (2.13) [11].

$$z_i = \frac{x_i - \bar{x}}{s} \tag{2.11}$$

where z_i is the Z-Score of the i-th object, x_i is the original value of the i-th object, $\bar{x}$ is sample average of the variable, and s is sample standard deviation of the variable.

$$\bar{x} = \frac{\sum_{j=1}^{k} x_j}{k} \tag{2.12}$$

$$s = \sqrt{\frac{\sum_{j=1}^{k} (x_j - \bar{x})^2}{k}} \tag{2.13}$$

where $\bar{x}$ is the arithmetic mean of the dataset, s is the standard deviation, x_j represents an individual data point at the index j, and k is the total number of data points in the set, with the summation indicating that the operation is performed for all data points from $j = 1, 2, \ldots, k$.

2.4 Gaussian Naive Bayes

Naive Bayes Classification, an algorithm that classifies data based on the calculations of class probability and sums up the combination of values from the data. Naive Bayes classification has stable accuracy results. However, Naive Bayes produces several conditions that will result in low accuracy if features and data parameters are added. For numerical data, Probability Density Function (PDF) can be used to calculate class probability values. PDF function represent the known data distribution. The following is the PDF formula shown in Equation (2.14) [2].

$$P\left(X_j = x_j | Y = y_l\right) = \frac{1}{\sqrt{2\pi s}} e^{-\frac{(x_j - \bar{x})^2}{2s^2}} \tag{2.14}$$

where P is probability, X_j is attribute, x_j is attribute value, Y the connected class, y_l is the connected sub-class.

2.5 Feature Importance

Feature Importance was quantified using a mean difference approach that measures the separation between classes by calculating the absolute difference in mean values across the two target labels. For each feature, the importance score was calculated by Equation (2.15).

$$FI_i = |\bar{x}_i(Label\ 1) - \bar{x}_i(Label\ 0)| \tag{2.15}$$

This formulation is conceptually aligned with the Normalized Mean Difference (NMD) method addressed by [3], which measures discriminative ability through between-class mean separation. Features with larger absolute differences exhibit stronger discriminatory power, reflecting clearer distinctions between class distributions. The implementation involved partitioning data by labels, computing class means, and ranking features by their absolute differences.

2.6 Confusion Matrix

Confusion Matrix is an evaluation method used to measure the classification performance of a model. Through this table, the model's performance can be assessed using statistical metrics such as accuracy (overall proportion of correct predictions), sensitivity (correctly identify positive prediction), specitivity (correctly identify negative prediction). The confusion matrix for two-class classification are tabulated in Table 1 [21].

Table 2.1. Confusion Matrix

		Prediction Class	
		Positive	Negative
Actual Class	Positive	TP	FP
	Negative	FN	TN

According to [15], True Positive (TP) is the number of data correctly predicted as positive, False Negative (FN) is positive data incorrectly predicted as negative, False Positive (FP) is negative data incorrectly predicted as positive, while True Negative (TN) is the number of data correctly predicted as negative. Based on these four values, accuracy, sensitivity, and specificity can be calculated through Equation (2.16), (2.17), and (2.18) [15].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2.16}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2.17}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2.18}$$

2.7 Independent Samples T-Test

The independent samples t-test, specifically the Welch's T-test variant is a parametric statistical inferential tool used to determine whether there is a statistically significant difference between the means of two unrelated groups [19]. The test statistics for Welch's Independent Samples T-test is defined by Equation (2.19) [10]. Where $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the groups, s_1^2 and s_2^2 are the sample variances of each group, n_1 and n_2 are the sample sizes in each group. The p-value represents the probability of observing the calculated t-stat.

$$t - stat = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{2.19}$$

3. MAIN RESULTS

3.1 Data Extraction

This research utilized RStudio software, where the code script and data could be accessed in https://github.com/risgunstat/GNB-stock-screening. The sample used in this study consists of 25 stocks selected from stocks indexed by SRI-KEHATI from the latest official report published by the Indonesian Stock Exchange on June 2, 2025. These stocks were chosen because the index emphasizes sustainable investment principles, where the selected stocks are tabulated in Table 3.1.

Table 3.1. List of Company Name

Stock	Company Name	Stock	Company Name
ANTM	Aneka Tambang Tbk.	INDF	Indofood Sukses International Tbk.
ASII	Astra International Tbk.	INTP	Indocement Tunggal Prakarsa Tbk.
AUTO	Astra Otoparts Tbk.	JSMR	Jasa Marga Tbk.
AVIA	Avia Avian Tbk.	KLBF	Kalbe Farma Tbk.
BBCA	Bank Central Asia Tbk.	MTEL	Dayamitra Telekomunikasi Tbk.
BBNI	Bank Negara Indonesia Tbk.	PGEO	Pertamina Geothermal Energy Tbk.
BBRI	Bank Rakyat Indonesia Tbk.	SIDO	Industri Jamu dan Farmasi Sido Tbk.
BBTN	Bank Tabungan Negara Tbk.	SMGR	Semen Indonesia Tbk.
BMRI	Bank Mandiri Tbk.	SMSM	Selamat Sempurna Tbk.
DSNG	Dharma Satya Nusantara Tbk.	SSMS	Sawit Sumbermas Sarana Tbk.
EMTK	Elang Mahkota Teknologi Tbk.	UNTR	United Tractors Tbk.
ICBP	Indofood CBP Sukses Makmur Tbk.	UNVR	Unilever Indonesia Tbk.
INCO	Vale Indonesia Tbk.		

From those 25 selected stocks in Table 3.1, the fundamental data were obtained from the Indopremier website (www.indopremier.com/ipotnews/newsSmartSearch.php?), where each company's data can be accessed by appending a stock specific code parameter (e.g., ?code=antm). The dataset includes market indicators, namely PBV, ROA, DER, and EPS. These indicators were collected on a quarterly basis, where the dataset spans five consecutive quarters (Q1 2024, Q2 2024, Q3 2024, Q4 2024, and Q1 2025) as training dataset for Naive Bayes Classification and Q2 2025 was reserved as the testing period to evaluate the model's predictive performance. The descriptive summary of the fundamental dataset for each period is tabulated in Table 3.2.

Table 3.2. Fundamental Ratio Descriptive Summary

Variable	Statistics	Q1 2024	Q2 2024	Q3 2024	Q4 2024	Q1 2025	Q2 2025
PBV	Mean	2.7172	3.3964	2.7708	2.966	2.0448	2.6996
	Min	0.54	0.52	0.53	0.46	0.37	0.35
	Max	21.26	40.34	24.54	33.46	14.28	26.7
ROA	Mean	0.0204	0.0388	0.0585	0.0775	0.0224	0.0453
	Min	0.0019	0.0033	0.0046	0.0064	0.0006	0.0005
	Max	0.0918	0.1592	0.1973	0.2972	0.0695	0.1645
DER	Mean	2.2168	2.284	2.0752	2.1816	2.1392	2.2224

Variable	Statistics	Q1 2024	Q2 2024	Q3 2024	Q4 2024	Q1 2025	Q2 2025
	Min	0.12	0.1	0.08	0.13	0.1	0.09
	Max	13.85	13.68	13.22	13.42	12.97	13.29
EPS	Mean	119.218	240.6472	402.9496	503.9884	112.5452	244.33
	Min	4.24	2.45	7.22	23.95	6.26	5.88
	Max	1228.98	2576.26	4213.96	5278.7	861.47	2197.31

In addition to the fundamental dataset, technical indicators were computed based on historical price and volume data of the selected stocks and the Jakarta Composite Index (IHSG) as the market benchmark. The technical dataset was extracted from the Yahoo Finance platform covering the period from January 2024 to July 2025. Several indicators were aggregated on a quarterly basis to align with the fundamental data and the classification periods used in the study. The descriptive summary of the technical indicators is tabulated in Table 3.3.

Table 3.3. Technical Ratio Descriptive Summary

Variable	Stat	Q1 2024	Q2 2024	Q3 2024	Q4 2024	Q1 2025	Q2 2025
Average Log Return	Mean	-0.00003	-0.00177	0.00092	-0.00109	-0.00203	0.00142
	Min	-0.00516	-0.00882	-0.00480	-0.00388	-0.00805	-0.00391
	Max	0.00362	0.00429	0.00430	0.00278	0.00363	0.01216
Average Volume	Mean	34856450	48748650	37083991	37373726	44948306	56403556
	Min	1865734	2804827	2375728	1594529	987824	1547249
	Max	134254148	360402167	236396795	248714471	307207893	261814041
Average Price	Mean	4640.42	4287.92	4476.63	4534.21	3994.40	3932.34
	Min	488.24	402.38	410.22	450.55	398.48	432.82
	Max	23578.45	23150.96	25536.54	26852.82	24368.10	21936.76
Average Beta	Mean	0.83161	0.83161	0.83161	0.83161	0.83161	0.83161
	Min	0.06603	0.06603	0.06603	0.06603	0.06603	0.06603
	Max	1.39147	1.39147	1.39147	1.39147	1.39147	1.39147
Average Moving Average	Mean	4633.07	4390.11	4399.96	4574.80	4097.88	3896.68
	Min	482.18	413.16	406.61	465.34	396.29	426.89
	Max	23412.31	23600.36	24779.90	26919.17	24949.33	22239.78
Average RSI	Mean	49.12	44.77	53.36	46.54	43.21	52.47
	Min	33.04	25.63	34.41	38.17	27.03	42.35
	Max	65.60	63.69	62.15	58.13	56.41	67.62

Variable	Stat	Q1 2024	Q2 2024	Q3 2024	Q4 2024	Q1 2025	Q2 2025
Average MACD	Mean	-0.13073	-1.16300	0.52476	-0.44283	-1.68354	1.00587
	Min	-4.22922	-5.80402	-2.82649	-2.39013	-4.69775	-1.67945
	Max	2.73615	2.60629	2.15634	3.30845	4.45663	8.06191

From both fundamental and technical datasets, a binary classification label was assigned to each observation. The labeling process utilized the stocks's average logarithmic return (Avg_LogReturn) of each stock in the subsequent period, allowing every quarter's data to serve as a predictor of future market performance. Specifically, the Avg_LogReturn from the following quarter was used as the labeling reference, where positive values (Label = 1) indicate investable stocks and negative values (Label = 0) indicate non-investable stocks. The frequency of each label in every period is tabulated in Table 3.4.

From Table 3.4, the proportion of Label 1 and Label 0 fluctuates over time, reflecting the dynamic behavior of market sentiment throughout January 2025 to September 2025. Notably, Q2 2024 shows the highest number of positively labeled stocks suggesting a stronger market phase, while Q4 2024 records the fewest, indicating a possible downturn or correction period.

Table 3.4. Frequency Label Summary by Period

Period	Q1 2024	Q2 2024	Q3 2024	Q4 2024	Q1 2025	Q2 2025
Label 1	6 Stocks	17 Stocks	8 Stocks	5 Stocks	15 Stocks	16 Stocks
Label 0	19 Stocks	8 Stocks	17 Stocks	20 Stocks	10 Stocks	9 Stocks

3.2 Training Gaussian Naive Bayes Classification

The Gaussian Naive Bayes (GNB) classification model was trained using both fundamental and technical indicators to identify the most influential financial variables in predicting quarterly stock performance. Prior to classification, all eleven predictor variables were standardized with Z-Score normalization. This step was critical because the dataset integrated features with vastly different scales and units of measure such as large technical indicators like Average Volume and constrained fundamental indicators like ROA. By standardizing the data, we eliminated magnitude disparity to ensure that all features contributed equally to the model.

The model utilized eleven predictor variables, comprising four fundamental indicators and seven technical indicators such as PBV, ROA, DER, EPS, Average Log Return, Average Volume, Average Price, Beta, Average Moving Average, Average Relative Strength Index, and Average Moving Average Convergence Divergence. The classification analysis was performed across five consecutive quarters, from Q1 2024 to Q1 2025. The resulting confusion matrix heatmaps are presented in Figure 3.1.

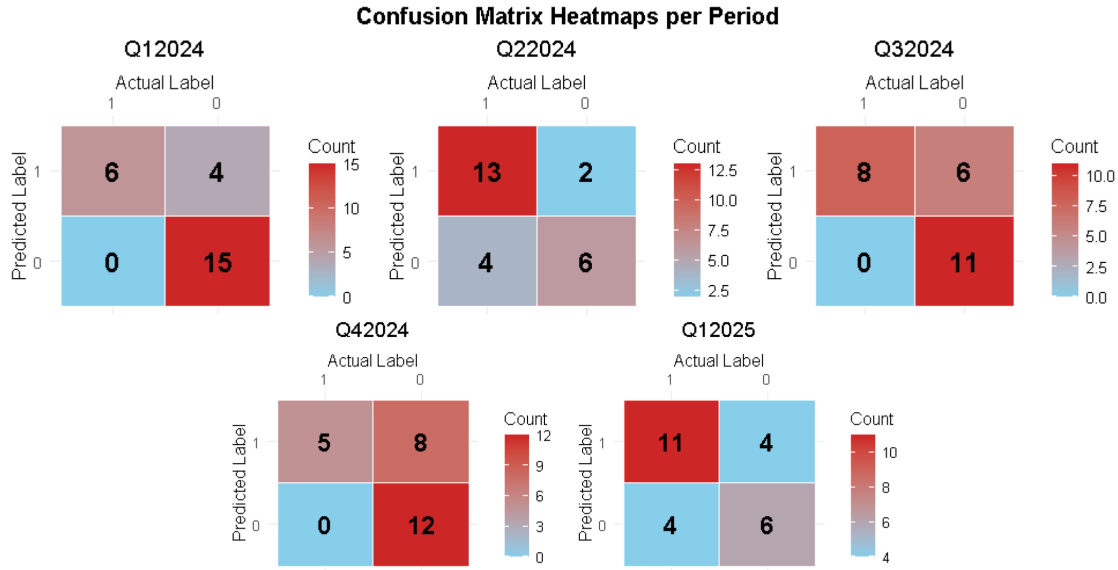

Figure 3.1. Confusion Matrix Heatmaps by Period

From Figure 3.1, the model's classification performance is highly dynamic as its most frequent correct prediction shifts between True Negative and True Positives across the periods. This fluctuation strongly suggests significant underlying volatility and shifts within the data's class distribution or returns. Furthermore, the model shows notable stability by perfectly capturing all actual positive return (Label = 1) in three out of five quarters. The metrics value from the confusion matrix and the feature importance of each period are presented in Figure 3.2.

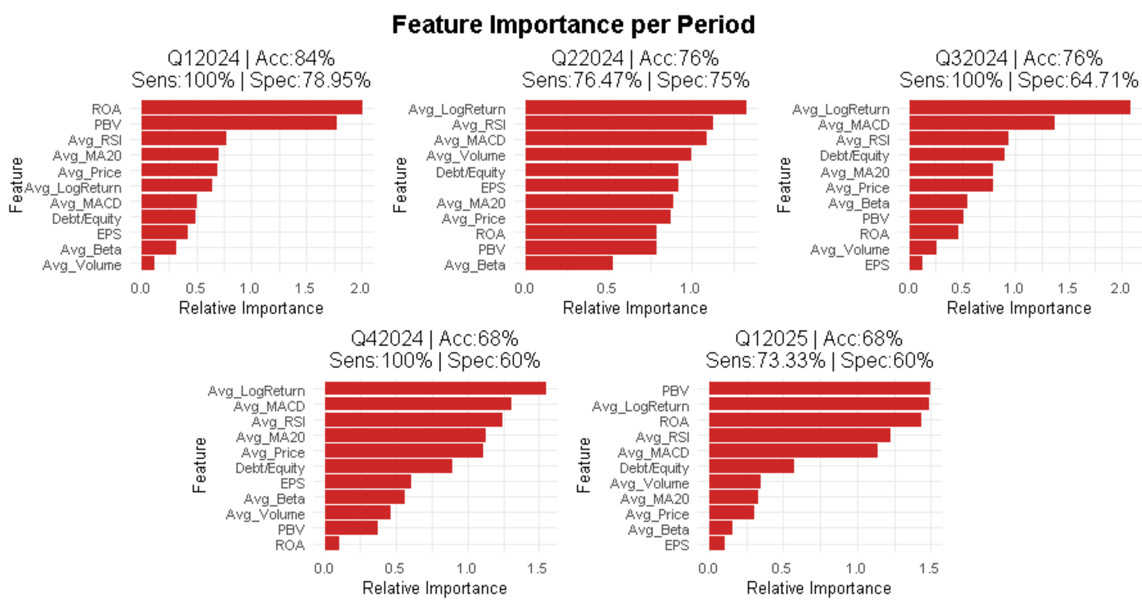

Figure 3.2. Plot Feature Importance by Period

Based on Figure 3.2, the Naive Bayes model demonstrates an average accuracy of 74,4%, despite a steady decline from 84% (Q1 2024) to 68% (Q1 2025) reflecting increasing market volatility. Sensitivity metrics reveal an exceptional value, maintaining 100% in most periods (Q1

2024, Q3 2024, and Q4 2024), which signifies the model's ability to identify investable stocks. However, the gradual decrease in specificity from 78.95% (Q1 2024) to 60% (Q1 2025) suggests a growing susceptibility to false positives.

Figure 3.2 also shows that the dominance of explanatory variables tends to shift over time. In Q1 2024, fundamental indicators like ROA and PBV played a stronger role in determining stock classification accuracy. However, starting from Q2 2024, technical indicators such as Log Return, MACD, RSI began to exhibit greater influence on the model's predictive capability. This transition suggests that market behavior changes to short-term trading momentum rather than fundamentals. The average feature importance for every training period is presented in Figure 3.3.

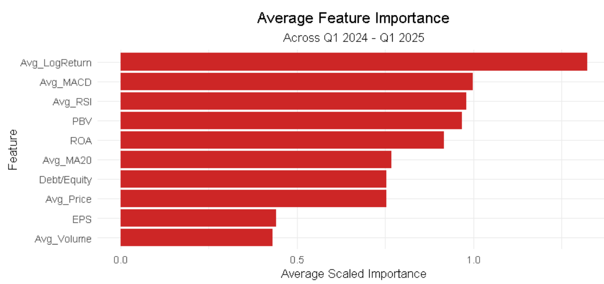

Figure 3.3. Plot Average Feature Importance

Figure 3.3 shows that Avg_LogReturn holds the highest contribution to the model, followed by Avg_MACD and Avg_RSI, reflecting the strong influence of technical indicators. Meanwhile, PBV and ROA emerge as the most influential fundamental variables, suggesting that valuation and profitability ratios still play a complementary role alongside market dynamics. After the fifth feature, the importance values decline significantly, suggesting that additional variables offer limited additional information to the classification process. Therefore, the top five variables were selected as the core predictors for the testing classification.

3.3 Testing Gaussian Naive Bayes Classification

Testing classification aims to evaluate the predictive performance to identify profitable stocks for the upcoming quarter. After being trained on five historical periods (Q1 2024 - Q1 2025), the model was applied to the most recent dataset (Q2 2025). The testing model was constructed using the five most influential features identified in the training classification, namely Avg_LogReturn, Avg_MACD, Avg_RSI, PBV, and ROA. The Q2 2025 dataset was intentionally prepared without actual label values, representing an unseen future period that the model seeks to predict. This design simulates a real world investment scenario, where portfolio decisions are made based on available fundamental and technical indicators without knowledge of futures. The testing results of the testing classification model are summarized Table 3.5.

Table 3.5. Label Result for Testing Classification

Stock	Prob Label 0	Prob Label 1	Stock	Prob Label 0	Prob Label 1
ANTM	**0.963**	0.037	INDF	**0.608**	0.392
ASII	0.367	**0.633**	INTP	**0.570**	0.430
AUTO	0.484	**0.516**	JSMR	0.377	**0.623**
AVIA	**0.622**	0.378	KLBF	**0.796**	0.204
BBCA	**0.519**	0.481	MTEL	0.415	**0.585**

Stock	Prob Label 0	Prob Label 1	Stock	Prob Label 0	Prob Label 1
BBNI	0.471	**0.529**	PGEO	**0.902**	0.098
BBRI	0.479	**0.521**	SIDO	**0.530**	0.470
BBTN	**0.801**	0.199	SMGR	**0.579**	0.421
BMRI	0.483	**0.517**	SMSM	**0.696**	0.304
DSNG	0.398	**0.602**	SSMS	0.257	**0.743**
EMTK	0.399	**0.601**	UNTR	0.315	**0.685**
ICBP	0.436	**0.564**	UNVR	**0.945**	0.055
INCO	**0.760**	0.240			

From Table 3.5, the model classified 12 stocks into the investable category (Label 1) and 13 stocks into the non-investable category (Label 0). The investable stocks are SSMS, UNTR, ASII, JSMR, DSNG, EMTK, MTEL, ICBP, BBNI, BBRI, BMRI, AUTO. Then, the non-investable stocks are BBCA, SIDO, INTP, SMGR, INDF, AVIA, SMSM, INCO, KLBF, BBTN, PGEO, UNVR, and ANTM. The predicted probabilities indicate varying confidence levels across stocks, where SSMS, UNTR, and ASII exhibit strong probabilities toward the investable category indicating stronger return prospects. In contrast, stocks such as ANTM, UNVR, PGEO show dominant probabilities under non-investable categories indicating weaker return prospects in the following quarter.

3.4 Simple Portfolio Simulation

Further evaluation of the model's practical applicability was performed through a simple portfolio simulation covering the period from April 1, 2024, to September 30, 2025. The cumulative performance from each periods are presented in Figure 3.4.

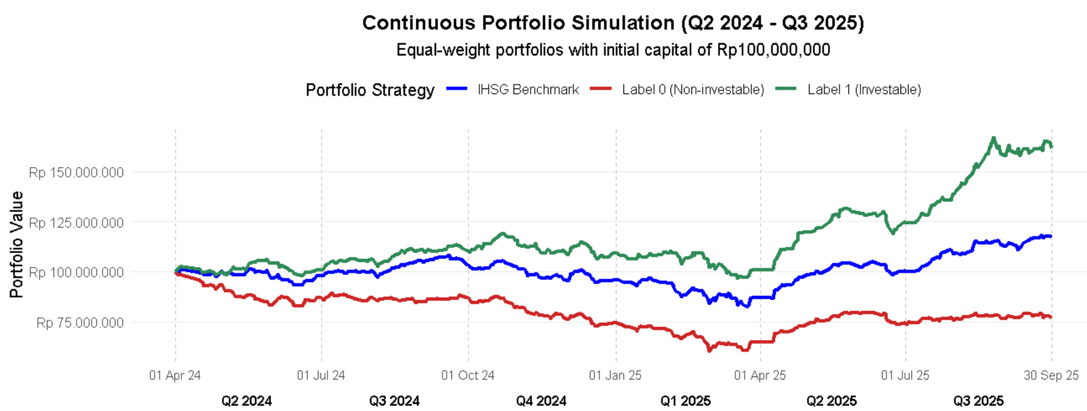

Figure 3.4. Line Chart of Continuous Portfolio Simulation

This simulation employed a quarterly rebalancing mechanism, where the portfolio constituents were adjusted at the beginning of each quarter based on the model's updated classifications. The simulations started with an initial capital of IDR 100 milion distributed equally across all stocks identified as investable and non-investable category. Based on Figure 3.4, the portfolio simulation demonstrates strong predictive accuracy of the Gaussian Naive Bayes in identifying high-performance securities. The investable portfolio exhibited a consistent upward trend, significantly outperforming both the market benchmark and the non-investable group. On the contrary, the non-investable group remained consistent below the initial capital which indicate the model's effectiveness in filtering out underperforming stocks. While Figure 3.4 illustrates the cumulative performance, Figure 3.5 provides a focused of Q3 2025 period to highlight recent predictive accuracy.

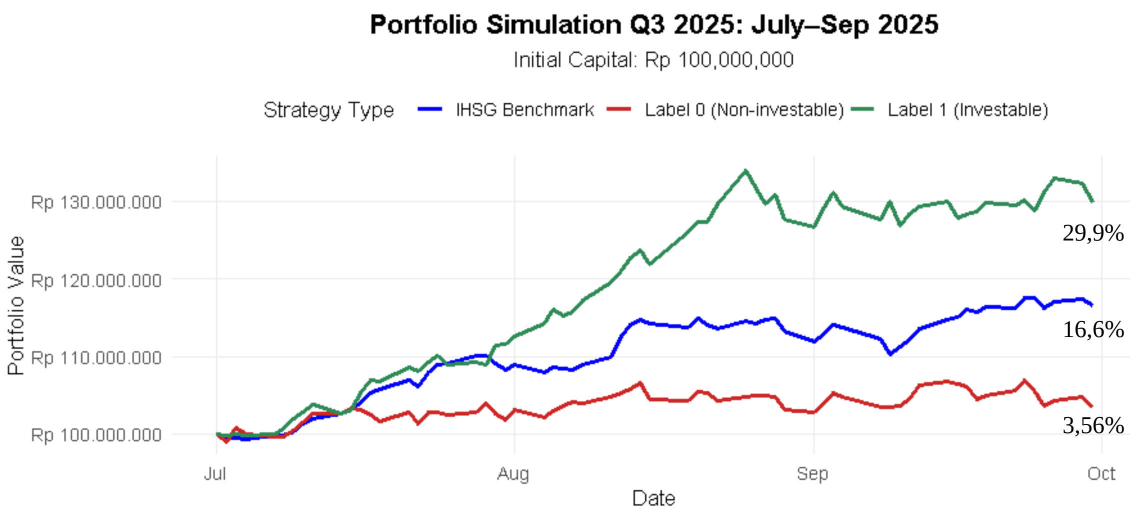

Figure 3.5. Line Chart of Q3 2025 Portfolio Simulation

From Figure 3.5, the investable portfolio achieved the strongest performance with a return of 29.9%, substantially outperforming the IHSG Benchmark which generated 16.6% and the non-investable stocks which recorded only a 3.56% return. While this performance gap visually confirms the model's capability, the mathematical significance of these differences is validated via Welch's Independent Samples T-Test as detailed in Table 3.6.

Table 3.6. Welsh's Independent T-Test Value

Period	Avg Return Label 1	Avg Return Label 0	Avg Return IHSG	$t-stat$	$p-value$
Q2 2024	0.93%	-13.02%	-1.96%	2.910	0.0056
Q3 2024	9.55%	-0.19%	5.44%	1.957	0.0357
Q4 2024	-1.13%	-14.17%	-7.36%	3.255	0.0020
Q1 2025	-7.87%	-13.20%	-9.11%	0.988	0.1675
Q2 2025	23.72%	15.02%	15.54%	0.641	0.2655
Q3 2025	29.87%	3.56%	16.57%	1.673	0.0592

Based on Table 3.6, the model demonstrates strong statistical significance ($p-value < 0.05$) in Q2 2024, Q3 2024, Q3 2024. Furthermore, while the Q3 2025 period yields a $p-value$ of 0.0592, it is considered marginally significant, indicating a high probability that the observed performance is driven by the model's predictive power rather than random variance. This consistent pattern across multiple period, provides the empirical confirmation that the classification is a reliable tool for investment decision.

These results suggest that integrating the classification model's output into investment decision making processes could generate and enhance portfolio returns beyond passive index strategies. The portfolio results should be interpreted within the broader market environment in Indonesia during Q3 2025. The IHSG showed signs of recovery after a period of weakness in the earlier quarter. Several large cap sectors displayed improving performance, particularly companies with stable operational fundamentals. This general market improvement supports the stronger returns observed in the investable portfolio which includes stocks with solid financial indicators and consistent trading activity. Stocks such as SSMS, UNTR, and ASII recorded higher predicted probabilities in the classification step. Their positive contribution to the portfolio return is consistent with their recent performance trends in the market.

The effectiveness of the model is also reflected in how it identified stocks with stable fundamentals and clearer price movements. Momentum indicators such as MACD and RSI tend to perform well when price trends become more defined. This may help explain why the model classified stocks like ASII, UNTR, and BBRI as investable. These stocks also maintained relatively stable profitability indicators such as ROA. In contrast several non investable stocks such as UNVR, ANTM, and PGEO showed weaker or less consistent performance signals which aligns with the lower predicted probabilities produced by the model.

Overall the portfolio results and the market context show that the classification framework can work as a practical screening tool under market conditions where trends and fundamental signals are stable. The alignment between model predictions and the observed performance of Indonesian large cap stocks during Q3 2025 suggests that the approach has potential value for stock selection in the local market. However the results should still be interpreted with caution because they are based on a limited time period and a specific market phase.

4. CONCLUSION

This study successfully achieves its objective of developing a stock screening framework using the Gaussian Naive Bayes classifier to classify SRI-KEHATI constituents based on combined fundamental and technical indicators. The empirical results show that the proposed model is effective in identifying stocks that are both sustainable and financially attractive, demonstrating that machine learning can enhance the selection process within ESG-oriented portfolios. The portfolio simulation results further support the model's practical relevance, where the investable portfolio consistently outperforms both the benchmark and the non-investable group. Importantly, the independent t-test confirms that the return differences between these portfolios are statistically significant, providing strong inferential evidence that the model captures genuine predictive signals rather than random variation. This strengthens the argument that sustainability-based screening, when combined with data-driven techniques, can deliver superior investment outcomes.

These findings contribute to the broader development of responsible investment practices in Indonesia by offering a quantitative method that aligns sustainability objectives with return maximization. The study also reinforces the shift from traditional qualitative ESG screening toward more rigorous, systematic, and analytics-based decision frameworks that can strengthen investor confidence and potentially accelerate capital flows into ESG-compliant assets.

This research also has several limitations that should be acknowledged. The model was evaluated using only five quarters of data which may not fully capture long term market cycles or structural changes in the Indonesian economy. The portfolio simulation relied on an equal-weighted strategy and a short three month holding period which limits its ability to represent real world investment constraints. In addition, the classification labels were constructed solely from historical return without incorporating risk measures which may introduce bias during periods of market volatility.

These constraints suggest several directions for future research. Testing alternative machine learning algorithms such as Random Forest, Support Vector Machine, or ensemble approaches may improve classification accuracy when longer datasets become available. Expanding the feature space to include macroeconomic indicators, sentiment variables, and real time ESG rating changes would help the model reflect broader market conditions and structural shifts that weren't captured in this study. Future work should also examine different portfolio construction methods and extend the holding period to provide a more realistic assessment of investment outcomes. Finally, evaluating the model's robustness across varying market regimes, particularly during stress periods and by testing additional indices, would strengthen its generalizability and practical relevance for investors in the Indonesian capital market.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest

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