KSÜ Mühendislik Bilimleri Dergisi, 29(3), 2026
Araştırma Makalesi

KSU J Eng Sci, 29(3), 2026
Research Article

Kahramanmaras Sutcu Imam University
Journal of Engineering Sciences

Geliş Tarihi : 22.10.2025
Kabul Tarihi : 24.06.2026

Received Date : 22.10.2025
Accepted Date : 24.06.2026

AN EXPLAINABLE MACHINE LEARNING APPROACH USING FUNDAMENTAL RATIOS FOR STOCK RETURN PREDICTION AND PORTFOLIO REBALANCING

TEMEL ORANLAR KULLANILARAK HISSE SENEDI GETIRI TAHMINI VE PORTFÖY YENIDEN DENGELEME IÇIN AÇIKLANABILIR BIR MAKINE ÖĞRENIMI YAKLAŞIMI

Mustafa ETCİL[1] (ORCID: 0000-0002-5573-3418)
Burak KOLUKISA[2] *(ORCID: 0000-0003-0423-4595)*
Burcu BAKIR-GÜNGÖR[1] *(ORCID: 0000-0002-2272-6270)*

[1] *Abdullah Gul University, Department of Computer Engineering, Kayseri, Turkey*
[2] *Kayseri University, Department of Software Engineering, Kayseri, Turkey*

*Sorumlu Yazar / Corresponding Author: Mustafa ETCİL, mustafa.etcil@agu.edu.tr

ABSTRACT

This research develops an explainable ensemble learning framework to forecast stocks' market-relative performance and guide portfolio rebalancing in Borsa Istanbul (BIST). The analysis covers quarterly data from 20 firms between 2009-Q1 and 2025-Q1 and employs Random Forest, XGBoost, LightGBM, and CatBoost trained on thirteen financial ratios. Hyperparameters are selected using grid search with time-series cross-validation, and performance is evaluated out-of-sample. Portfolios are rebalanced quarterly using predicted returns and benchmarked against an equally weighted portfolio and the BIST 100 Index. Results show that model-based portfolios generally outperform benchmarks in total return and risk-adjusted performance, with stronger statistically supported results in broader Top-k configurations, particularly CatBoost Top-7. SHAP identifies profitability and valuation indicators, especially return on assets, return on equity, and key valuation ratios, as the main drivers of future stock performance. These findings support explainable ensemble learning for fundamental-based portfolio management in emerging markets.

Keywords: Explainable machine learning, portfolio rebalancing, fundamental analysis, ensemble models, stock return prediction

ÖZET

Bu çalışma, hisse senetlerinin piyasa göreli performansını tahmin etmek ve Borsa İstanbul'da (BIST) portföy yeniden dengelemesini yönlendirmek amacıyla açıklanabilir ensemble öğrenme çerçevesi geliştirmektedir. Analiz, 2009-Q1–2025-Q1 döneminde 20 firmanın çeyreklik verilerini kapsamakta ve on üç finansal oranla eğitilen Random Forest, XGBoost, LightGBM ve CatBoost algoritmalarını kullanmaktadır. Hiperparametreler zaman serisi çapraz doğrulamalı grid search ile seçilmekte, performans örneklem dışı dönemde değerlendirilmektedir. Portföyler tahmin edilen getirilere göre çeyreklik yeniden dengelenmekte ve eşit ağırlıklı portföy ile BIST 100 Endeksi'yle karşılaştırılmaktadır. Bulgular, model tabanlı portföylerin toplam getiri ve risk ayarlı performansta karşılaştırma stratejilerini geride bıraktığını; daha güçlü ve istatistiksel olarak desteklenen sonuçların geniş Top-k konfigürasyonlarında, özellikle CatBoost Top-7'de görüldüğünü göstermektedir. SHAP analizi, aktif kârlılığı, özkaynak kârlılığı ve temel değerleme oranlarını gelecekteki hisse performansının başlıca belirleyicileri olarak göstermektedir.

Anahtar Kelimeler: Açıklanabilir makine öğrenimi, portföy yeniden dengeleme, temel analiz, topluluk modelleri, hisse senedi getiri tahmini

This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

INTRODUCTION

Portfolio construction is a central problem in financial decision-making, involving the allocation of capital across assets to achieve a balance between expected return and risk (Fabozzi & Markowitz, 2011). Following the mean–variance framework proposed by Markowitz, portfolio optimization aims to manage this trade-off through efficient asset allocation (Markowitz, 1990). The overall performance of a portfolio, however, largely depends on the accurate identification of stocks with high return potential, as stock selection directly influences investment outcomes (Kalayci et al., 2019). To support these decisions, two main analytical approaches are commonly applied: fundamental and technical analysis (Nti et al., 2020). Fundamental analysis assesses a firm's intrinsic value through financial indicators such as profitability, leverage, liquidity, and dividend policy, making it more suitable for medium- to long-term investment horizons. Technical analysis, in contrast, relies on price behavior, trading volume, and momentum indicators to capture short-term market movements.

As financial markets evolve under changing economic conditions, investors periodically adjust portfolio allocations to maintain the desired balance between risk and return (Dai et al., 2024). The frequency of rebalancing varies across investment strategies and market environments, with adjustments typically occurring on a daily, monthly, or quarterly basis (Zilbering et al., 2015). In recent years, advances in computational methods have encouraged the application of machine learning (ML) to stock selection and portfolio management. ML models can process large and complex datasets, identify nonlinear patterns among financial variables, and support more systematic investment decisions (Novykov et al., 2025; Sutiene et al., 2024; Gunjan & Bhattacharyya, 2023). Several studies have examined such applications in different market contexts. In (Silva et al., 2015), the authors proposed a hybrid optimization framework that combines fundamental and technical indicators within a multi-objective evolutionary algorithm. Using S&P 500 data from 2010 to 2014, the model optimized return and risk jointly by blending financial ratios—such as return on equity, profit margin, and price-to-earnings ratio—with trading rules like moving averages and stop-loss thresholds. The resulting portfolios, rebalanced daily to incorporate new information, consistently outperformed the S&P 500 benchmark with higher returns and lower volatility. Similarly, (Huang et al., 2021) compared several ML algorithms—including feed-forward neural networks, random forests, and adaptive neuro-fuzzy inference systems—for long-term stock prediction based on fundamental analysis. Drawing on 22 years of quarterly data from S&P 100 companies, the authors found that ML models, particularly random forests, produced more accurate return forecasts and yielded superior risk-adjusted performance relative to market benchmarks. Building on this line of research, (Tsai et al., 2023) examined the performance of various ML architectures—Random Forest, Feedforward Neural Network, Gated Recurrent Unit, and Financial Graph Attention Network—for stock selection in the Taiwan market. Using 18 financial indicators as model inputs, the top-ranked portfolios achieved higher excess returns and Sharpe ratios than the TW50 index. Further studies have extended these applications to portfolio optimization. In (Huang et al., 2025), predicted returns generated by OLS-H, Random Forest, and LSTM models from firm-level indicators were incorporated into a mean–variance framework for CSI 300 constituents, with monthly rebalancing enhancing both cumulative and risk-adjusted returns. Likewise, (Liu et al., 2021) introduced a hybrid Enhanced Grey Wolf Optimizer–Support Vector Regression (EGWO–SVR) framework that integrates metaheuristic search with ML for stock selection. The EGWO component simultaneously performs parameter calibration and feature subset selection for the SVR predictor, thereby enhancing its forecasting capability. Empirical analyses on large-cap stocks from the U.S. and Chinese A-share markets demonstrated that the EGWO–SVR portfolios achieved consistently higher cumulative and risk-adjusted returns than benchmark indices and competing algorithms such as GA-, PSO-, and GSA-based models. Finally, (Paiva et al., 2019) developed a Support Vector Machine–based trading system integrated with the Markowitz mean–variance model. Using daily data from the Brazilian Ibovespa index between 2001 and 2016, the study applied monthly rebalancing to optimize the risk–return trade-off, and the proposed framework achieved consistently higher cumulative and risk-adjusted returns than conventional strategies.

Prior research has shown that ML can enhance portfolio construction by capturing complex patterns in financial data. However, most existing studies focus on developed markets and give limited attention to model interpretability. The lack of explainable approaches reduces transparency in investment decisions, making it difficult to identify the underlying financial factors driving model predictions. In this study, an explainable ML framework is developed for predicting stocks' performance relative to the market and guiding portfolio rebalancing in the Borsa Istanbul (BIST) market—an emerging market that has received relatively little attention in the literature. The analysis covers 20 firms with consistent financial disclosures over the 2009–2025 period, and portfolios are rebalanced on a quarterly basis in line with the prediction horizon. Thirteen fundamental indicators are employed as explanatory variables, representing valuation, profitability, liquidity, leverage, and dividend policy dimensions. Four ensemble learning models—Random Forest, XGBoost, LightGBM, and CatBoost—are implemented to generate next-quarter forecasts, with model parameters determined through a systematic validation procedure that respects the temporal ordering of the data. Stocks are ranked according to the predicted values and selected to construct Top-k portfolios with different numbers of constituent stocks. Portfolio performance is evaluated using standard investment metrics and benchmark comparisons to assess both return and risk-adjusted outcomes. In addition, the analysis examines the sensitivity of results to portfolio size and weighting scheme, and applies bootstrap tests to evaluate the statistical significance of return differences. Model interpretability is achieved through SHAP, which quantifies the relative contribution of each financial indicator to the prediction outcomes.

In the remainder of this paper, Section 2 describes the data, preprocessing steps, and the overall methodological framework, including the ML models, portfolio construction and rebalancing strategy, backtesting procedure, and evaluation metrics. Section 3 presents the empirical results, covering both model-based portfolio performance and the explainability analysis. Finally, Section 4 concludes the study and outlines potential directions for future research.

MATERIAL AND METHODS

This section outlines the empirical framework of the study, detailing the data foundation, modeling methodology, and evaluation protocols. The analysis utilizes firm-level quarterly fundamentals from the BIST market as inputs to a set of tree-based ensemble learning models aimed at predicting stock performance in relation to the market. The following subsections describe the preparation of the dataset, the structure of the predictive models, the construction and rebalancing of portfolios, and the backtesting approach adopted to assess their performance. Finally, the empirical framework incorporates a SHAP-based explainability analysis to interpret model predictions and highlight the fundamental factors that are most influential in forecasting stock returns. An overview of the research design, including the sequence of data processing, modeling, and evaluation stages, is presented in Figure 1.

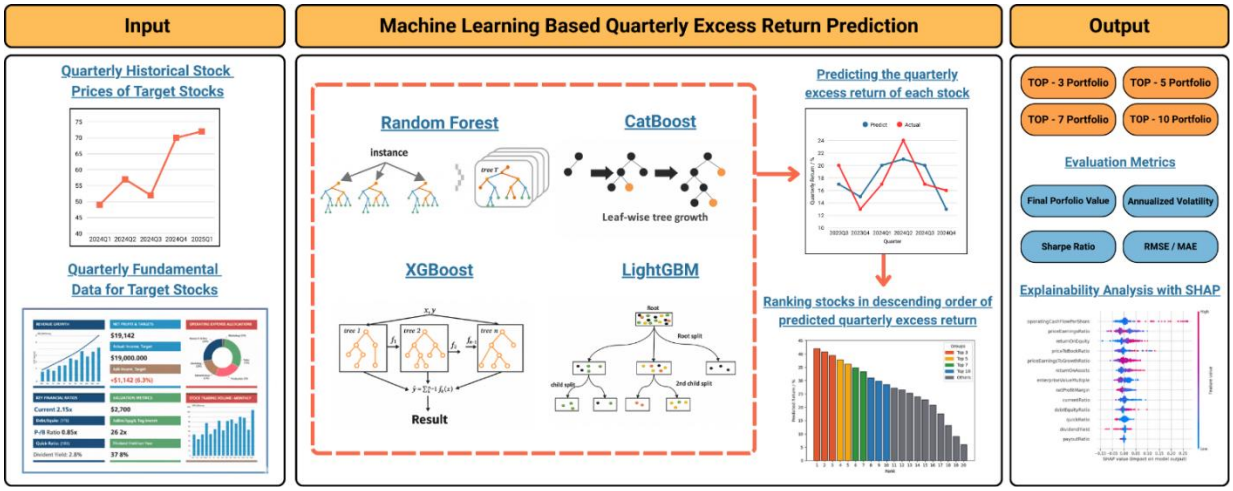

Figure 1. Overview of the Research Design Including Data, Modeling, and Evaluation Steps

Data Description and Preprocessing

In this study, firm-level quarterly financial and price data were collected for a selected group of twenty companies listed on the BIST 100 Index. The sample comprises firms with continuous quarterly financial disclosures over the 2009–2025 period and includes companies characterized by relatively high market capitalization and active trading in the Turkish equity market. The compilation of companies, encompassing various sectors such as banking, manufacturing, telecommunications, and energy, is presented in Table 1. The data were retrieved from two complementary sources. Fundamental information, consisting of thirteen pre-calculated financial ratios for each firm and quarter, was obtained from the Financial Modeling Prep API (Financial Modeling Prep, 2025), while quarterly closing prices were retrieved from Yahoo Finance (yfinance, 2025) to assess stock performance and construct market-adjusted return measures. The two datasets were aligned by firm and quarter to establish an integrated time-series framework connecting each company's financial fundamentals with its subsequent relative performance. Each quarterly observation aligns with the standard reporting dates of Turkish companies: 31 March, 30 June, 30 September, and 31 December.

Table 1. List of Selected Companies Analyzed in This Study

AGHOL_IS	AKBNK_IS	ARCLK_IS	ASELS_IS	CIMSA_IS
DOAS_IS	DOHOL_IS	EGEEN_IS	ENKAI_IS	EREGL_IS
GARAN_IS	GUBRF_IS	HEKTS_IS	MGROS_IS	SAHOL_IS
TCELL_IS	TOASO_ IS	TTKOM_IS	TUPRS_IS	ZOREN_IS

The thirteen financial ratios, outlined in Table 2, represent five essential elements of corporate performance: liquidity, profitability, leverage, valuation, and dividend policy. Collectively, they provide a comprehensive view of companies' financial stability, operational effectiveness, and value creation. Liquidity and profitability ratios evaluate a company's short-term stability and earnings potential, while leverage and cash-flow metrics assess financial risk and funding flexibility. Valuation metrics demonstrate the market's pricing of companies in relation to their fundamentals, whereas dividend ratios indicate shareholder return policies.

Table 2. Financial Ratios Used in The Study

Category	Financial Ratio	Calculation
Liquidity Ratios	Current Ratio	Current Assets / Current Liabilities
	Quick Ratio	(Current Assets - Inventories) / Current Liabilities
Profitability Ratios	Return on Equity (ROE)	Net Income / Shareholders' Equity
	Return on Assets (ROA)	Net Income / Total Assets
	Net Profit Margin	Net Income / Revenue
Leverage and Cash Flow Ratios	Debt-to-Equity Ratio	Total Debt / Shareholders' Equity
	Operating Cash Flow per Share	Operating Cash Flow / Shares Outstanding
Valuation Ratios	Price-to-Earnings (P/E) Ratio	Market Price per Share / Earnings per Share
	Price-to-Book (P/B) Ratio	Market Price per Share / Book Value per Share
	Enterprise Value Multiple (EV/EBITDA)	Enterprise Value / EBITDA
	Price/Earnings to Growth (PEG) Ratio	(Market Price per Share / EPS) / Earnings Growth

Dividend Ratios	Dividend Yield	Dividend per Share / Market Price per Share
	Payout Ratio	Dividend per Share / Earnings per Share

Prior to model implementation, various preprocessing procedures were conducted to guarantee the dataset's completeness and analytical consistency. Missing values in the financial ratios were addressed through a two-stage imputation methodology. A forward-fill method was utilized within each firm's time series to extend the most recent valid observation. Subsequently, any remaining missing entries were substituted with the median of the relevant ratio. This method maintained the temporal integrity of the data while reducing possible biases from outliers. All variables were then organized within a quarterly framework and aligned by firm and reporting date to maintain chronological consistency.

The subsequent quarter's excess return, defined as the difference between the realized stock return and the corresponding BIST 100 Index return, was used as the target variable. This specification reduces the influence of market-wide fluctuations and directs the models toward cross-sectional variation in firm-level performance. The excess return for firm $\boldsymbol{i}$ at time $\boldsymbol{t}$ is defined as in Equation (1):

$$\boldsymbol{ER_{i,t+1} = R_{i,t+1} - R_{m,t+1}} \quad (1)$$

where $\boldsymbol{R_{i,t+1}}$ denotes the stock return of firm $\boldsymbol{i}$ between quarters $\boldsymbol{t}$ and $\boldsymbol{t+1}$, and $\boldsymbol{R_{m,t+1}}$ represents the corresponding return of the BIST 100 Index over the same period. Utilizing the subsequent quarter's outcome as the forecasting target guarantees that only information accessible at the conclusion of quarter $\boldsymbol{t}$ is included in the model estimation process, thus preventing look-ahead bias.

To evaluate predictive performance, the dataset was partitioned chronologically into a training period spanning 2009-Q1 to 2021-Q4 and an out-of-sample testing period covering 2022-Q1 to 2024-Q4. Feature scaling was conducted subsequent to this split to preserve temporal ordering. Standardization was employed to enhance comparability across financial ratios and facilitate stable model estimation. Each feature was transformed as in Equation (2):

$$\boldsymbol{x' = \frac{(x - \mu_{train})}{\sigma_{train}}} \quad (2)$$

where $\boldsymbol{\mu_{train}}$ and $\boldsymbol{\sigma_{train}}$ denote the mean and standard deviation estimated from the training sample. Figure 2 illustrates the overall preprocessing workflow, encompassing data preparation, target definition, scaling procedures, and chronological sample partitioning.

Quarterly Stock Prices and Return Calculations

Stock	Quarter	Stock Price	Bist 100 Price	Stock Return (%)	Index Return (%)	Excess Return (%)
ASELS.IS	2009-Q1	47.83	3,850	+17.49	+9.61	+7.88
ASELS.IS	2009-Q2	56.20	4,220	+15.46	+7.24	+8.22
...	...	...	...	...	...	...
ASELS.IS	2024-Q4	123.50	9,820	-2.66	+7.33	-9.99
ASELS.IS	2025-Q1	120.21	10,540	-	-	-
TUPRS.IS	2009-Q1	15.20	3,850	+6.45	+9.61	-3.16
TUPRS.IS	2009-Q2	16.18	4,220	+2.50	+7.24	-4.74
...	...	...	...	...	...	...
TUPRS.IS	2024-Q4	34.20	9,820	+5.70	+7.33	-1.63
TUPRS.IS	2025-Q1	36.15	10,540	-	-	-

Scaled Fundamental Financial Ratios and Target Variable

Stock	Quarter	P/E	P/B	ROA	ROE	...	Quick Ratio	Excess Return (%)
ASELS.IS	2009-Q1	0.84	-0.32	-0.41	-0.38	...	0.62	+7.88
ASELS.IS	2009-Q2	-0.51	0.17	-0.28	0.11	...	1.04	+8.22
...	...	...	...	...	...	...	...	...
ASELS.IS	2024-Q4	1.23	0.89	0.14	0.31	...	-0.43	-9.99
TUPRS.IS	2009-Q1	-0.63	-0.74	-0.18	-0.52	...	0.31	-3.16
TUPRS.IS	2009-Q2	-0.29	-0.91	0.33	-0.44	...	0.18	-4.74
...	...	...	...	...	...	...	...	...
TUPRS.IS	2024-Q4	1.47	0.63	0.42	0.29	...	-0.67	-1.63

Split the data for each stock:
2009-Q1 to 2021-Q4 : Train, 2022-Q1 to 2024-Q4 : Test

Figure 2. Overview of Data Preprocessing, Including Target Variable Construction, Feature Scaling, and Sample Partitioning.

Machine Learning Models for Stock Return Prediction

This study employs four tree-based ensemble learning algorithms—Random Forest, XGBoost, LightGBM, and CatBoost—to model and predict next-quarter excess returns, as these approaches are widely adopted in machine learning-based financial forecasting research (Basak et al., 2019; Krauss et al., 2017). These algorithms extend traditional decision-tree methodologies by combining multiple learners within an ensemble framework, enabling the capture of nonlinear relationships commonly observed in financial data while supporting stable predictive performance. Random Forest constructs multiple decision trees trained on bootstrap samples, while random feature selection at each split reduces inter-tree correlation and enhances generalization performance (Breiman, 2001). Gradient boosting–based models, including XGBoost, LightGBM, and CatBoost, build trees sequentially by fitting new models to the residuals of previous iterations. XGBoost incorporates regularization and tree pruning to control model complexity and enhance computational efficiency (Chen & Guestrin,2016), whereas LightGBM adopts a leaf-wise tree growth strategy combined with histogram-based feature binning to accelerate training while maintaining performance (Ke et al., 2017). CatBoost further extends the boosting framework through ordered boosting and symmetric tree structures designed to address estimation bias (Prokhorenkova et al., 2017).

Table 3. Hyperparameter Search Spaces for the Machine Learning Models

Model	Hyperparameter	Value
XGBoost	n_estimators	[100, 200]
	learning_rate	[0.01, 0.05]
	max_depth	[2, 3, 4]
	min_child_weight	[5, 10, 20]
	subsample	[0.7, 0.8]
	colsample_bytree	[0.7, 0.8]
	reg_lambda	[1, 3, 5]
LightGBM	n_estimators	[100, 200]
	learning_rate	[0.01, 0.05]
	max_depth	[2, 3, 4]
	num_leaves	[7, 15]
	min_child_samples	[10, 20, 30]
	subsample	[0.7, 0.8]
	colsample_bytree	[0.7, 0.8]
	reg_alpha	[0.1, 1, 5]
	reg_lambda	[0.1, 1, 5]
Random Forest	n_estimators	[100, 200, 300]
	max_depth	[3, 4, 5]
	max_features	['sqrt', 'log2']
	min_samples_split	[10, 20, 30]
	min_samples_leaf	[5, 10, 15]
CatBoost	iterations	[200, 400]
	learning_rate	[0.01, 0.05]
	depth	[3, 4, 5]
	l2_leaf_reg	[3, 5, 10, 15]
	subsample	[0.7, 0.8]

Model estimation was performed within a time-series cross-validation framework that maintains the temporal sequence of the data. Hyperparameters were determined using grid search combined with a five-fold time-series cross-validation method utilizing TimeSeriesSplit in scikit-learn. In this expanding-window framework, each validation fold was designed to utilize prior observations for predicting future periods, thus preserving chronological

integrity during model selection. The hyperparameter search spaces for each algorithm were established to balance model flexibility and computational efficiency, with the relevant grids detailed in Table 3. The final model configurations were established based on cross-validated performance in the training sample and then evaluated on the out-of-sample test set.

Portfolio Construction and Rebalancing Strategy

The portfolio construction process is directed by the excess return predictions produced by the machine learning models. At the end of each quarter, each model produces a predicted next-quarter excess return for all firms in the sample. Based on these forecasts, stocks are ranked in descending order of expected relative performance, and portfolios are formed by selecting the top-ranked stocks. To examine the robustness of the results and to identify the optimal portfolio size that balances return potential and diversification, four portfolio configurations are evaluated, comprising the Top-3, Top-5, Top-7, and Top-10 ranked stocks. In the baseline portfolio construction approach, all selected stocks receive equal weights, meaning that each stock contributes the same proportion of capital regardless of its predicted return. This design allows the analysis to focus on the ranking ability of the machine learning models rather than on an additional portfolio optimization procedure and ensures consistent comparability across different portfolio sizes. To further assess the robustness of the portfolio construction rule, an additional ablation analysis is conducted using prediction-based weighting. In this alternative specification, portfolio weights are assigned proportionally to the predicted excess returns generated by the corresponding machine learning model. The performance of prediction-weighted portfolios is subsequently compared with that of the baseline equal-weighted portfolios to evaluate the impact of the weighting scheme on portfolio outcomes. Portfolios are updated at the end of each quarter according to the most recent model forecasts. This quarterly rebalancing process follows a fixed schedule consistent with firms' financial reporting cycles and ensures that the portfolio composition reflects the latest available fundamental information. Once new return predictions are obtained, stocks are re-ranked, and holdings are replaced for the upcoming quarter. The rebalancing procedure, therefore, represents a systematic and rule-based mechanism for translating model outputs into investment decisions.

Backtesting and Evaluation Metrics

The backtesting framework assesses the predictive accuracy of machine learning models and the economic performance of portfolios derived from their forecasts. Forecast accuracy is evaluated through Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), calculated for both the training and out-of-sample test datasets to provide a comparative analysis of in-sample fitting and out-of-sample efficacy. RMSE is defined as in Equation (6):

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{6}$$

where y_t denotes the realized excess return, $\hat{y}_t$ the predicted excess return, and T the number of observations in the respective evaluation sample. MAE is given by Equation (7):

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t| \tag{7}$$

Together, these metrics quantify the magnitude of prediction errors and offer complementary measures of model accuracy. Beyond statistical performance, the economic value of the forecasts is evaluated through a quarterly rebalancing simulation. Each portfolio starts with an initial capital of 100,000 units. During the out-of-sample period, portfolios are formed at the end of each quarter using predicted excess returns and are held for the following quarter. Holdings are then updated according to revised forecasts. Transaction costs are assumed to be zero, allowing portfolio performance to reflect only the contribution of model-generated signals. Portfolio performance is evaluated using cumulative and risk-adjusted measures. Total Return (TR), capturing overall portfolio growth during the evaluation horizon, is defined as in Equation (8):

$$TR = \frac{V_t - V_0}{V_0} \tag{8}$$

where V_t and V_0 represent the final and initial portfolio values, respectively. Annualized Return (AR) represents the compounded average yearly rate of return over the entire horizon, as shown in Equation (9):

$$AR = (1 + TR)^{1/N} - 1 \tag{9}$$

where TR is the cumulative return, and N is the number of years. Sharpe Ratio (SR) evaluates risk-adjusted performance by relating excess portfolio return to its volatility, as defined in Equation (10):

$$SR = \frac{E[R_p - R_f]}{\sigma_p} \tag{10}$$

where R_p is the portfolio return, R_f is the risk-free rate, and σ_p is the portfolio volatility.

In addition to descriptive performance measures, statistical significance tests are conducted to assess whether the observed differences between model-based portfolios and benchmark strategies are statistically significant. A paired non-parametric bootstrap procedure is employed to estimate confidence intervals and p-values for the mean quarterly return differences between model-driven portfolios, the equal-weight benchmark portfolio, and the BIST 100 Index.

Portfolio performance is evaluated relative to two benchmark strategies: an equal-weighted portfolio of all twenty stocks and the BIST 100 Index. The equal-weighted portfolio serves as a passive diversification benchmark, while the BIST 100 Index represents overall market performance. These benchmarks provide reference points for comparing the return and risk characteristics of the model-based portfolios.

Explainability Analysis

This study employs the SHAP framework (Lundberg & Lee, 2017) to interpret model behavior and quantify the contribution of fundamental ratios to predicted excess returns. Rooted in cooperative game theory, SHAP decomposes model outputs by assigning each feature a marginal contribution to the forecast. In this setting, the analysis highlights which financial indicators—such as profitability, valuation, and leverage ratios—systematically influence model predictions, thereby providing an economically interpretable perspective on the sources of relative performance. The SHAP value for feature i is defined as in Equation (11):

$$\boldsymbol{\varphi_i} = \sum_{\boldsymbol{S} \subseteq \boldsymbol{F} \setminus \{\boldsymbol{i}\}} \left[\frac{|\boldsymbol{S}|!\,(|\boldsymbol{F}| - |\boldsymbol{S}| - \mathbf{1})!}{|\boldsymbol{F}|!}\right] \left[\boldsymbol{f}_{(\boldsymbol{S} \cup \{\boldsymbol{i}\})}(\boldsymbol{x}_{\boldsymbol{S} \cup \{\boldsymbol{i}\}}) - \boldsymbol{f}_{\boldsymbol{S}}(\boldsymbol{x}_{\boldsymbol{S}})\right] \tag{11}$$

where $\boldsymbol{F}$ denotes the set of all features, $\boldsymbol{S}$ represents a subset of features excluding $\boldsymbol{i}$, and $\boldsymbol{f}_{\boldsymbol{S}(\boldsymbol{x}_{\boldsymbol{S}})}$ is the model output based solely on features in $\boldsymbol{S}$. The resulting value $\boldsymbol{\varphi_i}$ measures the average marginal contribution of feature $\boldsymbol{i}$ to the prediction across all possible feature coalitions. This explainability analysis provides a transparent view of the underlying drivers of the models' forecasts and the portfolio rebalancing decisions derived from them.

EXPERIMENTAL RESULTS

This section presents the empirical results derived from the out-of-sample assessment of all machine learning models. The analysis initially assesses forecast accuracy and then evaluates the economic performance of portfolios constructed from predicted excess returns, comparing them to benchmark strategies. A SHAP-based interpretability analysis is performed to identify the key factors that consistently affect model predictions.

Forecast Performance Evaluation

This section assesses the predictive efficacy of the proposed ensemble learning models utilizing standard regression error metrics. Table 4 presents the RMSE and MAE values for both the training and out-of-sample testing periods. The results indicate that the four models exhibit comparable forecasting accuracy, with only small differences across algorithms. In the training sample, RMSE values range from 0.16281 to 0.16538, whereas MAE values range from 0.11257 to 0.11408. In the testing sample, RMSE values remain close to 0.23, ranging from 0.23336 to 0.23451, while MAE values vary between 0.17473 and 0.17553. Random Forest attains the lowest test RMSE, whereas LightGBM and CatBoost obtain the lowest test MAE values. Overall, the differences among models remain limited,

suggesting that no single algorithm exhibits a clear advantage based solely on statistical error metrics. The increase in prediction errors from the training to the test period is consistent with the out-of-sample nature of financial forecasting, where changing market conditions and time-varying cross-sectional relationships may affect model performance.

Table 4. Regression Performance Metrics Across Training and Test Samples

Model	Training RMSE	Training MAE	Test RMSE	Test MAE
XGBoost	0.16407	0.11336	0.23451	0.17522
LightGBM	0.16538	0.11408	0.23421	0.17473
Random Forest	0.16281	0.11257	0.23336	0.17553
CatBoost	0.16392	0.11327	0.23354	0.17473

Table 5 reports the optimal hyperparameter configurations selected through grid search with time-series cross-validation. The selected configurations indicate relatively controlled model complexity across all algorithms. XGBoost and LightGBM are both configured with low learning rates and shallow tree depths, while Random Forest uses a limited maximum depth together with a relatively large minimum leaf size. CatBoost is also estimated with a low learning rate, a limited number of iterations, and L2 regularization.

Table 5. Optimal Hyperparameter Configurations Selected via Grid Search

Model	Optimal Hyperparameters
XGBoost	colsample_bytree = 0.8; learning_rate = 0.01; max_depth = 3; min_child_weight = 5; n_estimators = 100; reg_lambda = 5; subsample = 0.8
LightGBM	colsample_bytree = 0.7; learning_rate = 0.01; max_depth = 3; min_child_samples = 20; n_estimators = 100; num_leaves = 15; reg_alpha = 1; reg_lambda = 0.1; subsample = 0.7
Random Forest	max_depth = 4; max_features = sqrt; min_samples_leaf = 15; min_samples_split = 10; n_estimators = 200
CatBoost	depth = 5; iterations = 200; l2_leaf_reg = 15; learning_rate = 0.01; subsample = 0.8

Portfolio Performance

The out-of-sample portfolio results summarized in Table 6 show how the machine learning models translate predicted excess returns into portfolio outcomes under the baseline equal-weighting rule. At each quarterly rebalancing date, stocks are ranked in descending order according to their predicted next-quarter excess returns, and the Top-3, Top-5, Top-7, and Top-10 portfolios are formed by selecting the first k stocks from this ranking. Within each Top-k portfolio, the selected stocks receive equal weights, so that the reported results reflect the effect of model-based stock ranking rather than an additional weighting or optimization procedure. The analysis therefore focuses on two dimensions: the comparative performance of the tree-based algorithms and the sensitivity of portfolio outcomes to the number of selected stocks. Performance is evaluated relative to an equal-weighted portfolio of all target stocks and the BIST 100 Index in terms of return and risk-adjusted performance.

Across most configurations, the model-based portfolios generate higher total and annualized returns than the benchmark strategies, although performance varies across algorithms and portfolio sizes. XGBoost records its highest total return in the Top-10 portfolio, with a final value of 853,158 TL and a total return of 753.16%, while its highest Sharpe ratio is obtained in the Top-7 portfolio at 1.70. LightGBM follows a similar return pattern, as the Top-7 and Top-10 portfolios produce almost identical total returns of 783.59% and 783.83%, respectively; however, the Top-7 portfolio yields the higher Sharpe ratio of 1.93. Random Forest reaches its strongest result in the Top-7 configuration,

with a final value of 884,591 TL, a total return of 784.59%, and a Sharpe ratio of 1.86, while CatBoost displays the highest overall performance in the same portfolio size, reaching 1,100,263 TL, a total return of 1,000.26%, and a Sharpe ratio of 1.95. These results indicate that portfolio performance does not follow a monotonic pattern with respect to k. Although Top-3 portfolios are formed from the stocks with the highest predicted excess returns in each quarter, they are also more concentrated, so their realized performance depends on a smaller number of stock-specific outcomes. As k increases, additional high-ranked stocks are included in the portfolio, changing the balance between concentration and diversification. In Table 6, this pattern is reflected by the stronger performance of Top-7 and Top-10 configurations relative to more concentrated alternatives in several cases. XGBoost obtains its highest total return in Top-10, LightGBM produces very similar total returns in Top-7 and Top-10, and Random Forest and CatBoost achieve their strongest results in Top-7. Therefore, the results do not indicate that more concentrated portfolios systematically outperform broader Top-k configurations; rather, the most favorable portfolio size varies across algorithms and performance criteria.

Table 6. Comparative Portfolio Performance of Machine Learning Models During the Out-of-Sample Period

Model	Portfolio	Final Portfolio Value (TL)	Total Return (%)	Annualized Return (%)	Sharpe Ratio
XGBoost	Top3	636,463	536.46	85.32	1.54
	Top5	602,245	502.25	81.94	1.33
	Top7	807,956	707.96	100.66	1.70
	Top10	853,158	753.16	104.34	1.69
LightGBM	Top3	720,781	620.78	93.17	1.60
	Top5	741,735	641.73	95.02	1.51
	Top7	883,588	783.59	106.74	1.93
	Top10	883,833	783.83	106.76	1.76
Random Forest	Top3	578,057	478.06	79.47	1.22
	Top5	765,625	665.63	97.09	1.65
	Top7	884,591	784.59	106.81	1.86
	Top10	867,880	767.88	105.50	1.81
CatBoost	Top3	543,564	443.56	75.83	1.26
	Top5	910,449	810.45	108.81	1.75
	Top7	1,100,263	1,000.26	122.42	1.95
	Top10	861,434	761.43	104.99	1.79
Equal Weight	-	594,296	494.30	81.13	1.38
BIST100 Index	-	432,486	332.49	62.93	1.23

Relative to the benchmarks, the equal-weight portfolio records a total return of 494.30% and a Sharpe ratio of 1.38, while the BIST 100 Index records a total return of 332.49% and a Sharpe ratio of 1.23. Each model-based configuration exceeds the BIST 100 Index in total return, and most configurations also outperform the equal-weight benchmark. The risk-adjusted results are also generally stronger for the model-based portfolios, with several configurations achieving Sharpe ratios above both benchmarks, particularly among the Top-7 portfolios. Overall, the relatively similar forecasting error metrics reported in Table 4 translate into different portfolio outcomes in Table 6. This indicates that out-of-sample portfolio performance is shaped not only by regression accuracy, but also by the cross-sectional ranking of stocks and the selected Top-k configuration. Figure 3 complements these results by illustrating the normalized cumulative return paths over time and providing a visual comparison between model-driven strategies and the benchmark portfolios.

Table 7 compares the baseline equal-weighted portfolios with prediction-weighted portfolios as part of an ablation analysis of the portfolio construction methodology. Prediction-weighted total return indicates the cumulative return

achieved when the stocks chosen in each Top-k portfolio are weighted according to their expected excess returns, rather than assigned equal weights. The findings suggest that prediction-based weighting alters portfolio results, yet it does not consistently surpass the equal-weighting method. In XGBoost, prediction weighting enhances total returns in the Top-3 and Top-5 portfolios, whereas the equal-weighted specification is slightly superior in the Top-7 and Top-10 portfolios. A similar trend is noted for Random Forest, wherein prediction weighting enhances the more concentrated Top-3 and Top-5 portfolios, while equal weighting yields superior results in the wider Top-7 and Top-10 portfolios. In LightGBM, prediction weighting yields minimal enhancements in Top-3 and Top-5, yet results in decreased returns and Sharpe ratios in Top-7 and Top-10. CatBoost exhibits variable outcomes: prediction weighting enhances Top-3, Top-5, and Top-10 returns, whereas the equal-weighted Top-7 portfolio persists as the most robust configuration overall. These findings support the use of equal weighting as the baseline portfolio construction rule, as it allows portfolio performance to be evaluated primarily on the basis of stock selection and ranking quality. By contrast, prediction-weighted portfolios introduce an additional allocation effect that does not produce a consistent performance advantage across models and portfolio sizes.

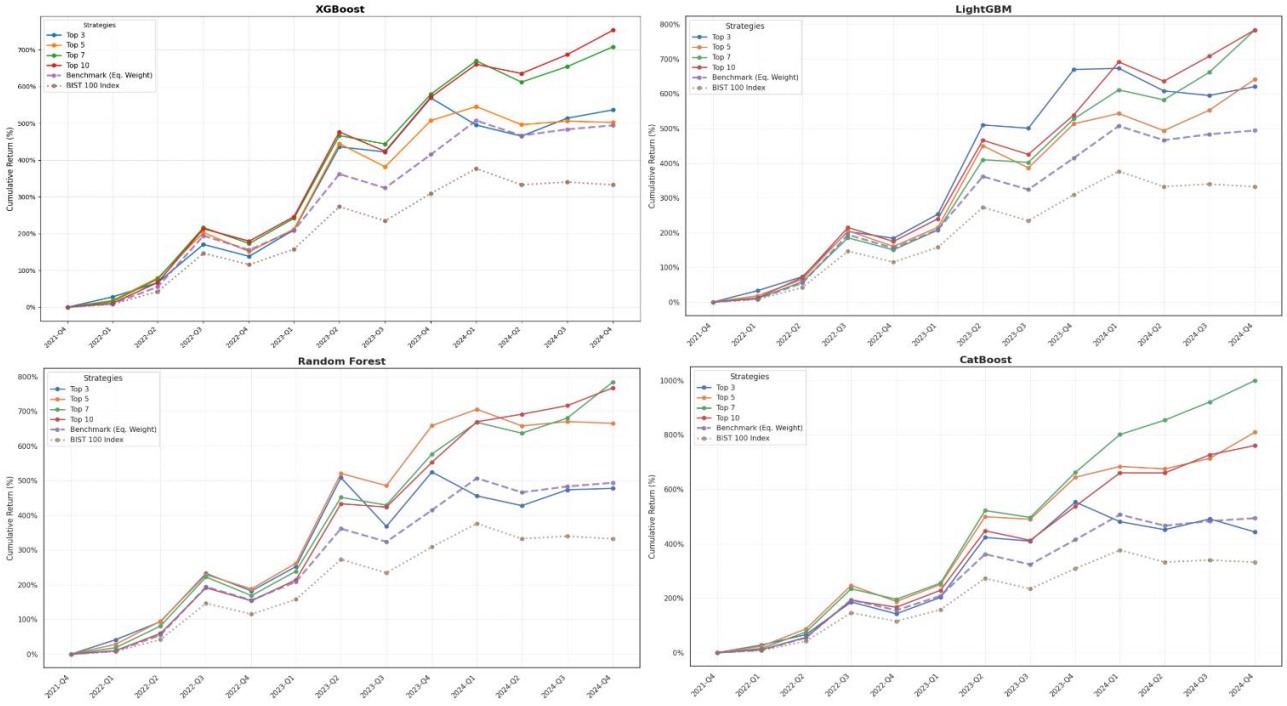

Figure 3. Normalized cumulative returns of XGBoost, LightGBM, Random Forest, and CatBoost strategies compared with the equal-weight benchmark and BIST 100 Index

Table 8 reports the paired bootstrap test results for the quarterly return differences between the model-based portfolios and the two benchmark strategies. The results show that statistical significance is more frequently observed against the BIST 100 Index than against the equal-weight benchmark. In particular, the Top-7 and Top-10 portfolios generally produce statistically significant positive return differences relative to the BIST 100 Index, with the strongest differences observed for CatBoost Top-7, LightGBM Top-10, Random Forest Top-7, and XGBoost Top-10. Comparisons with the equal-weight benchmark are more selective: statistically significant differences are observed mainly for the broader Top-k portfolios, including XGBoost Top-10, LightGBM Top-10, Random Forest Top-10, and CatBoost Top-7 and Top-10. Overall, the bootstrap results indicate that the model-based portfolios provide statistically stronger performance primarily in the Top-7 and Top-10 configurations, while the evidence is weaker for the more concentrated Top-3 and Top-5 portfolios.

SHAP-Based Interpretability Analysis

To improve interpretability, SHAP-based analyses were performed on all machine learning models to assess the impact of individual financial ratios on the prediction of next-quarter excess returns. Figure 4 presents the summary

plots that illustrate the marginal contribution of each feature to the model outputs. Notably, SHAP values indicate model-specific relationships rather than causal economic impacts; thus, the analysis emphasizes the relative significance of financial indicators within the predictive framework.

Table 7. Ablation Analysis of Equal-Weighted and Prediction-Weighted Top-k Portfolios

Model	Portfolio	Equal-weight Total Return (%)	Prediction-weighted Total Return (%)	Equal-weight Sharpe	Prediction-weighted Sharpe
XGBoost	Top3	536.46	558.43	1.54	1.54
	Top5	502.25	550.77	1.33	1.42
	Top7	707.96	704.14	1.70	1.70
	Top10	753.16	732.98	1.69	1.69
LightGBM	Top3	620.78	623.03	1.60	1.58
	Top5	641.73	651.55	1.51	1.53
	Top7	783.59	739.12	1.93	1.80
	Top10	783.83	748.21	1.76	1.72
Random Forest	Top3	478.06	539.00	1.22	1.32
	Top5	665.63	684.96	1.65	1.67
	Top7	784.59	761.56	1.86	1.82
	Top10	767.88	754.83	1.81	1.79
CatBoost	Top3	443.56	509.46	1.26	1.36
	Top5	810.45	823.01	1.75	1.77
	Top7	1000.26	964.95	1.95	1.92
	Top10	761.43	789.24	1.79	1.81

Table 8. Bootstrap Significance Tests For Quarterly Return Differences

Model	Portfolio	vs. Equal-Weight Benchmark Mean Diff. (%)	vs. BIST 100 Mean Diff. (%)
XGBoost	Top3	0.49 (p = 0.893)	4.10 (p = 0.305)
	Top5	0.59 (p = 0.872)	4.21 (p = 0.162)
	Top7	3.10 (p = 0.108)	6.72 (p < 0.001)***
	Top10	3.81 (p = 0.009)***	7.43 (p < 0.001)***
LightGBM	Top3	1.84 (p = 0.628)	5.46 (p = 0.088)*
	Top5	2.60 (p = 0.344)	6.22 (p = 0.022)**
	Top7	3.58 (p = 0.075)*	7.20 (p < 0.001) ***
	Top10	4.10 (p = 0.007)***	7.72 (p < 0.001)***
Random Forest	Top3	0.73 (p = 0.889)	4.35 (p = 0.343)
	Top5	2.61 (p = 0.439)	6.23 (p = 0.035)**
	Top7	3.88 (p = 0.073)*	7.50 (p < 0.001)***
	Top10	3.64 (p = 0.028)**	7.26 (p < 0.001)***
CatBoost	Top3	-0.56 (p = 0.885)	3.06 (p = 0.429)
	Top5	4.53 (p = 0.082)*	8.15 (p = 0.005)***
	Top7	6.39 (p < 0.001)***	10.00 (p < 0.001)***
	Top10	3.55 (p < 0.001)***	7.17 (p < 0.001)***

Note: Mean Diff. denotes the average quarterly return difference between the model-based portfolio and the corresponding benchmark. p-values are obtained from paired non-parametric bootstrap tests. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Across the models, profitability and valuation indicators appear among the most influential variables. Return on assets and return on equity are consistently ranked near the top, indicating that profitability-related measures play an important role in model predictions. Valuation indicators, including the price-to-earnings ratio, price-to-book ratio, and enterprise value multiple, also display relatively large SHAP distributions, suggesting that valuation characteristics contribute to the cross-sectional ranking of stocks. In several models, higher values of profitability variables are associated with positive SHAP contributions, whereas the direction and magnitude of valuation-related effects vary across indicators and algorithms. This pattern indicates that the models do not rely on a single financial ratio category, but combine profitability and valuation information when estimating expected excess returns. By contrast, liquidity, leverage, payout, and dividend-related variables generally exhibit smaller SHAP magnitudes. Variables such as the quick ratio, current ratio, debt-to-equity ratio, payout ratio, and dividend yield are positioned lower in the SHAP rankings and show more limited variation around zero. Operating cash flow per share, net profit margin, and the PEG ratio have some model-specific effects, but their overall contribution remains more moderate compared with the leading profitability and valuation indicators. Overall, the explainability results indicate that the prediction process is primarily shaped by profitability and valuation measures, while liquidity and dividend-related variables play a more limited role in distinguishing expected stock performance during the sample period.

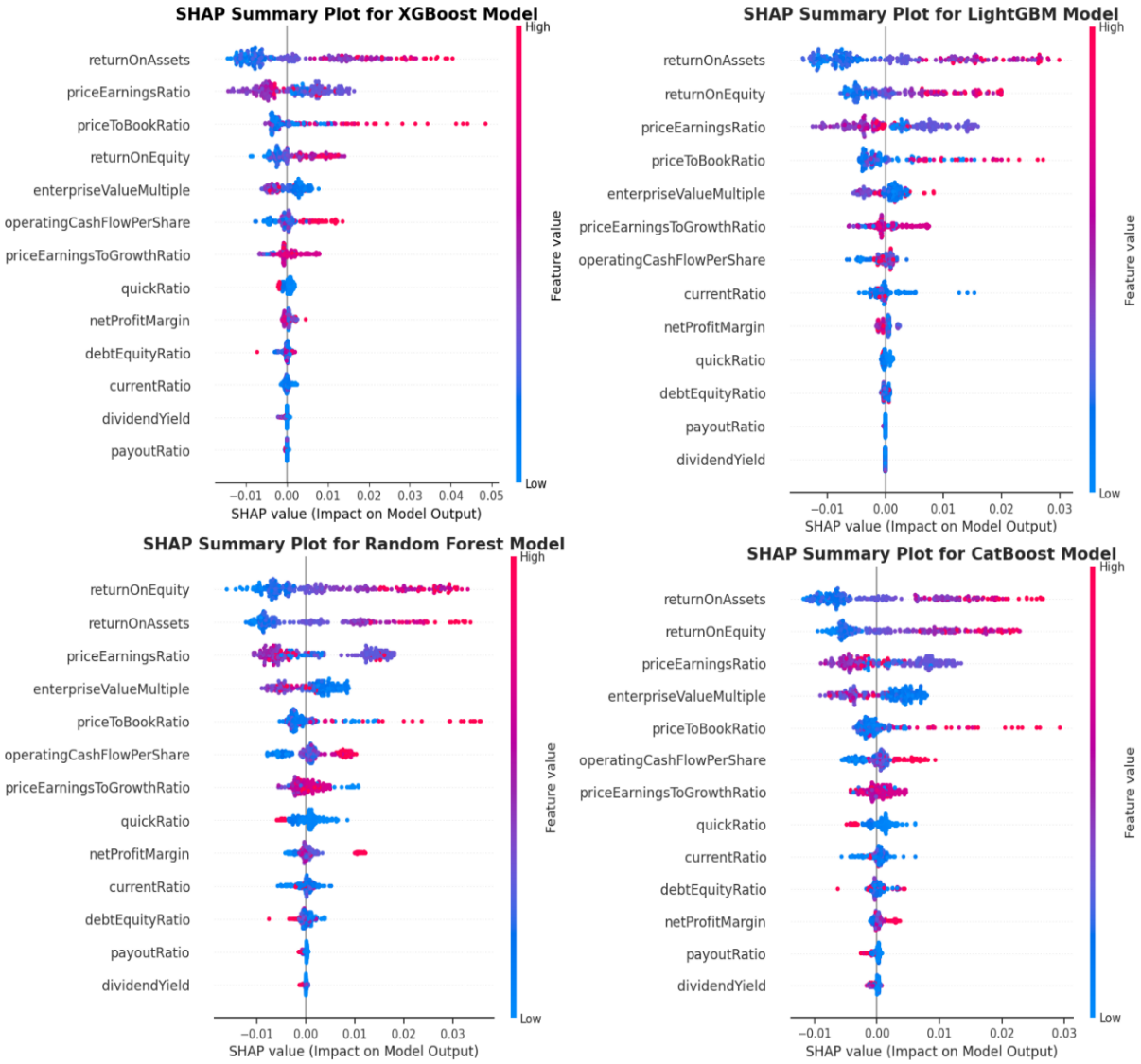

Figure 4. SHAP Summary Plots for the Machine Learning Models Used in the Study

CONCLUSION

This study investigates the efficacy of explainable ensemble learning models in forecasting next-quarter market-adjusted excess stock returns and informing quarterly portfolio rebalancing within the Borsa Istanbul market. Employing firm-level data from 20 companies over the period 2009Q1–2025Q1, four tree-based algorithms—Random Forest, XGBoost, LightGBM, and CatBoost—were trained on thirteen fundamental financial ratios encompassing liquidity, profitability, leverage, valuation, and dividend policy dimensions. The empirical framework employed a chronological experimental design, utilizing time-series cross-validation and hyperparameter optimization via grid search to maintain temporal consistency during model selection. At the end of each quarter, the models forecasted next-quarter excess returns, and portfolios were reconstructed by ranking stocks according to predicted values and assigning equal weights to the selected constituents. Out-of-sample backtesting over the 2022Q1–2024Q4 period indicates that most model-based portfolios outperformed the equal-weight benchmark portfolio and the BIST 100 Index in total return and risk-adjusted performance, although outcomes varied across models and portfolio sizes. CatBoost Top-7 produced the strongest overall result, reaching a total return of 1,000.26% and a Sharpe ratio of 1.95. LightGBM and Random Forest also achieved strong performance in the Top-7 and Top-10 configurations, while XGBoost recorded its highest total return in the Top-10 portfolio. The results further show that portfolio performance does not follow a fixed monotonic pattern with respect to k; more concentrated Top-3 portfolios do not systematically outperform broader configurations, and the most favorable portfolio size differs across algorithms and performance criteria. The ablation analysis comparing equal-weighted and prediction-weighted portfolios indicates that using predicted excess returns as portfolio weights changes portfolio outcomes but does not provide a consistent performance advantage across models and portfolio sizes. This supports the use of equal weighting as the baseline portfolio construction rule, as it allows portfolio performance to be evaluated primarily on the basis of stock selection and ranking quality. The bootstrap significance tests further show that statistically significant return differences are observed more frequently against the BIST 100 Index than against the equal-weight benchmark, particularly for Top-7 and Top-10 configurations. Moreover, SHAP analysis indicates that profitability and valuation metrics, particularly return on assets, return on equity, price-to-earnings ratio, price-to-book ratio, and enterprise value multiple, are among the most influential predictors of future excess returns. In contrast, liquidity, dividend-related, and some leverage indicators exhibit comparatively smaller contributions. Overall, the findings indicate that explainable ensemble learning models can support fundamental-based stock selection and quarterly portfolio rebalancing by combining predictive performance with interpretable financial signals. Future research may extend this framework by incorporating transaction costs, alternative optimization schemes, macroeconomic variables, and sentiment-based indicators to evaluate robustness across different market environments.

ACKNOWLEDGEMENT

This research was supported by the project titled "Sosyal Medya, Haber, Temel ve Teknik Analizleri Dikkate Alan Makine Öğrenmesi Temelli Hisse Senedi Yatırım Tavsiye Platformu" funded by the TUBITAK TEYDEB program under Project Number 3230482.

Artificial Intelligence Contribution Statement

This manuscript was conceived, written, and analyzed by the authors. Generative artificial intelligence tools were used only for language editing, paraphrasing, and improving textual fluency. They were not involved in study design, data analysis, interpretation of results, or figure preparation. All scientific content and methodological decisions were developed exclusively by the authors.

REFERENCES

Basak, S., Kar, S., Saha, S., Khaidem, L., & Dey, S. R. (2019). Predicting the direction of stock market prices using tree-based classifiers. The North American Journal of Economics and Finance, 47, 552–567. https://doi.org/10.1016/j.najef.2018.06.013.

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785–794). https://doi.org/10.1145/2939672.2939785.

Dai, T. S., Chen, B. J., Sun, Y. J., Yang, D. Y., & Wu, M. E. (2024). Constructing optimal portfolio rebalancing strategies with a two-stage multiresolution-grid model. Computational Economics, 64(5), 3117–3142. https://doi.org/10.1007/s10614-024-10555-y.

Fabozzi, F. J., & Markowitz, H. M. (Eds.). (2011). The theory and practice of investment management: Asset allocation, valuation, portfolio construction, and strategies (2nd ed.). John Wiley & Sons. https://doi.org/10.1002/9781118267028.

Financial Modeling Prep. *Financial Modeling Prep API: Documentation V2 – API Reference.* (2024). https://site.financialmodelingprep.com/developer/docs/ Accessed 04.05.25.

Gunjan, A., & Bhattacharyya, S. (2023). A brief review of portfolio optimization techniques. Artificial Intelligence Review, 56(5), 3847–3886. https://doi.org/10.1007/s10462-022-10273-7.

Huang, M., Dang, S., & Bhuiyan, M. A. (2026). Multi-objective portfolio optimization for stock return prediction using machine learning. Expert Systems with Applications, 298, 129672. https://doi.org/10.1016/j.eswa.2025.129672.

Huang, Y., Capretz, L. F., & Ho, D. (2021). Machine learning for stock prediction based on fundamental analysis. In 2021 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 1–10). IEEE. https://doi.org/10.1109/SSCI50451.2021.9660134

Kalayci, C. B., Ertenlice, O., & Akbay, M. A. (2019). A comprehensive review of deterministic models and applications for mean–variance portfolio optimization. Expert Systems with Applications, 125, 345–368. https://doi.org/10.1016/j.eswa.2019.02.011.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. Advances in Neural Information Processing Systems, 30. https://papers.nips.cc/paper/2017/hash/6449f44a102fde848669bdd9eb6b76fa-Abstract.html.

Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), 689–702. https://doi.org/10.1016/j.ejor.2016.10.031.

Liu, M., Luo, K., Zhang, J., & Chen, S. (2021). A stock selection algorithm hybridizing grey wolf optimizer and support vector regression. Expert Systems with Applications, 179, 115078. https://doi.org/10.1016/j.eswa.2021.115078.

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765–4774. https://papers.neurips.cc/paper_files/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html.

Markowitz, H. M. (1991). Foundations of portfolio theory. The Journal of Finance, 46(2), 469–477. https://doi.org/10.1111/j.1540-6261.1991.tb02669.x.

Novykov, V., Bilson, C., Gepp, A., Harris, G., & Vanstone, B. J. (2025). Deep learning applications in investment portfolio management: A systematic literature review. Journal of Accounting Literature, 47(2), 245–276. https://doi.org/10.1108/JAL-07-2023-0119.

Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. Artificial Intelligence Review, 53(4), 3007–3057. https://doi.org/10.1007/s10462-019-09754-z.

Paiva, F. D., Cardoso, R. T. N., Hanaoka, G. P., & Duarte, W. M. (2019). Decision-making for financial trading: A fusion approach of machine learning and portfolio selection. Expert Systems with Applications, 115, 635–655. https://doi.org/10.1016/j.eswa.2018.08.003.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: Unbiased boosting with categorical features. Advances in Neural Information Processing Systems, 31, 6638–6648. https://proceedings.neurips.cc/paper/2018/hash/14491b756b3a51daac41c24863285549-Abstract.html.

Silva, A., Neves, R., & Horta, N. (2015). A hybrid approach to portfolio composition based on fundamental and technical indicators. Expert Systems with Applications, 42(4), 2036–2048. https://doi.org/10.1016/j.eswa.2014.09.050.

Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., Kabasinskas, A., Tidjani, C., Ozturkkal, B., & Cerneviciene, J. (2024). Enhancing portfolio management using artificial intelligence: Literature review. Frontiers in Artificial Intelligence, 7, 1371502. https://doi.org/10.3389/frai.2024.1371502.

Tsai, P. F., Gao, C. H., & Yuan, S. M. (2023). Stock selection using machine learning based on financial ratios. Mathematics, 11(23), 4758. https://doi.org/10.3390/math11234758.

yfinance. *yfinance: Python Library for Yahoo! Finance Market Data.* (2025). https://pypi.org/project/yfinance/ Accessed 18.08.25.

Zilbering, Y., Jaconetti, C. M., & Kinniry, F. M., Jr. (2015). Best practices for portfolio rebalancing. Valley Forge, PA: The Vanguard Group. https://www.financieelonafhankelijkblog.nl/wp-content/uploads/2021/11/Vanguard-ISGPORE.pdf