Forecasting the XBANK Index in Türkiye Using Macroeconomic Indicators: A Model Comparison with Ensemble Learning Methods

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ABSTRACT

The objective of this study is to predict the monthly closing prices of the BIST Bank Index (XBANK) utilising macroeconomic and financial indicators. The explanatory variables encompass the real exchange rate, inflation, the consumer confidence index, the policy rate of the Central Bank of the Republic of Türkiye (CBRT), the growth rate of M2 money supply, CBRT reserves, deposits, the industrial production index, the Türkiye CDS spread, and the VIX fear index. In the initial evaluation, three machine learning models – GradientBoosting, XGBoost, and RandomForest Regressor – with the highest predictive power were identified using the LazyRegressor method, and hyperparameter optimization was performed on these models. The performance of the models was evaluated using the R^2 and RMSE criteria. The most successful result was obtained with the GradientBoosting model, which had an R^2 score of 0.99. Pursuant to feature importance analysis, it was determined that inflation (37%), policy interest rate (29%), and Central Bank of the Republic of Türkiye (CBRT) reserves (13%) were the variables exerting the most influence on the movements of the banking index. The findings of this study suggest that monetary policy and macroeconomic stability exert a significant influence on the stock performance of the Turkish banking sector.

Key words: *Stock Market Prediction, Machine Learning, XBANK, Gradient Boosting.*

JEL Codes: C53, G17, E44.

1. INTRODUCTION

Financial markets, particularly stock markets, play a pivotal role in modern economies by facilitating capital allocation, enabling risk sharing, and providing crucial signals for economic activity (Levine, 1997). Accurate forecasting of stock prices and indices is therefore of paramount importance to a wide range of stakeholders, including individual investors seeking to optimize portfolios, corporations making strategic financial decisions, and policymakers aiming to maintain economic stability (Timmermann and Granger, 2004). However, predicting market movements remains a formidable challenge due to the inherent characteristics of financial time series, which are often complex, noisy, non-linear, and highly sensitive to a multitude of factors ranging from macroeconomic fundamentals to shifts in investor sentiment (Malkiel, 2003; Shiller, 2002).

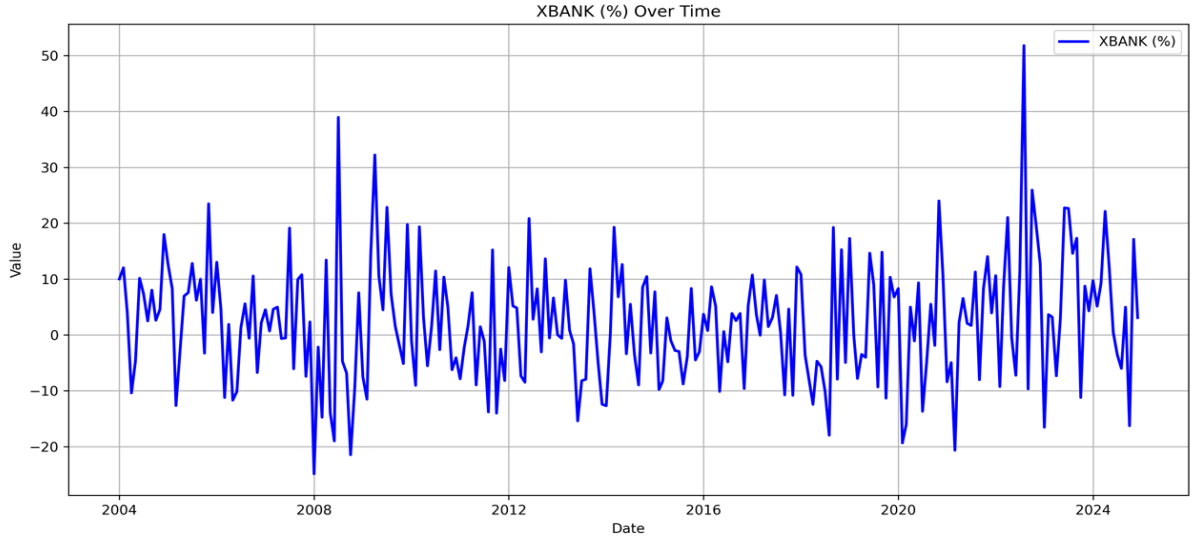
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Within the context of the Turkish economy, the banking sector occupies a central position, acting as the primary engine for financial intermediation and significantly influencing overall macroeconomic stability and growth. Consequently, the Borsa Istanbul (BIST) Bank Index (XBANK), which tracks the collective performance of banking stocks listed on the exchange, serves as a critical barometer for the health of both the financial system and the broader economy in Türkiye. Its movements reflect investor confidence in the banking sector and can foreshadow trends in credit availability, investment activity, and economic policy effectiveness. Understanding and anticipating the trajectory of the XBANK index is therefore vital.

Machine learning (ML) algorithms offer significant advantages over traditional econometric models in financial forecasting due to the inherent complexity of financial time series, which are often noisy, non-linear, and highly sensitive to numerous factors. Unlike econometric models that often rely on strict assumptions such as linearity, normality, and stationarity, ML techniques are adept at capturing intricate patterns and non-linear dependencies within large datasets without these restrictive assumptions. This flexibility allows ML models, particularly ensemble methods like Gradient Boosting and XGBoost, to potentially yield more accurate predictions in volatile market environments. Furthermore, ML algorithms can handle high-dimensional data, automatically manage missing values, and incorporate regularization techniques to mitigate overfitting, which are crucial for the nonstationary and volatile nature of financial time series. These capabilities enable ML models to overcome the limitations of conventional econometric approaches, leading to improved predictive power for complex financial data.

As illustrated in Figure 1, the return series of the BIST Bank Index exhibits significant volatility over time, characterized by sharp fluctuations, underscoring the challenges inherent in its prediction but also highlighting the potential rewards of accurate forecasting.

Figure 1. BIST Bank Index (%) Returns Over Time (2004-2024)



Source: Author's own work.

Accurate forecasts of the XBANK index can provide substantial benefits. For investors and financial institutions, such predictions are valuable for developing effective risk management strategies and optimizing portfolio allocations (Hull, 2012). For policymakers and regulators, anticipating index movements can offer insights into market reactions to policy changes and

aid in the early identification of potential systemic risks, thereby contributing to overall financial stability.

While traditional econometric models have long been employed for financial forecasting, the complexity and potential non-linearities within financial data, as evidenced in Figure 1, often limit their predictive power (Tsay, 2005). In recent years, the advent of sophisticated machine learning (ML) and ensemble learning techniques has offered promising alternatives. These methods are adept at capturing intricate patterns and dependencies within large datasets, potentially overcoming the limitations of conventional approaches and yielding more accurate predictions, particularly in volatile market environments (Gu et al., 2020; Fischer and Krauss, 2018).

The purpose of this study is to predict the value of the BIST Bank Index for the period 2004-2024 in Türkiye using machine learning methods and macroeconomic and financial indicators. By comparing various ML models, including ensemble techniques, this research aims to identify robust forecasting approaches for this critical Turkish financial index, leveraging key economic variables to enhance predictive accuracy. This investigation seeks to contribute not only to the academic literature on financial forecasting in emerging markets but also to provide practical insights for market participants operating within Türkiye.

This study makes a unique contribution to the extant literature by focusing specifically on the BIST Bank Index (XBANK), a critical barometer of Türkiye's financial health, and by providing a dedicated, long-term forecast over an extensive 20-year period (2004-2024). The study further enhances the field by comparing the performance of contemporary machine learning methods, including ensemble methods, in predicting this index. It offers valuable insights for risk assessment and informs policy considerations regarding financial stability in Türkiye.

The structure of this study comprises several sections, each meticulously designed to address a specific aspect of the forecasting of the XBANK index. The second section provides a detailed literature review, offering a comprehensive overview of previous research on stock market prediction, particularly within the Turkish context. In the third section, the data utilised is delineated, with a comprehensive exposition of the macroeconomic and financial indicators that have been selected for the analysis. The fourth section, entitled 'Methodology', provides a detailed exposition of the machine learning algorithms employed in the study. The fifth section of this study presents the empirical results. These results encompass a number of elements, including a comparative performance analysis, a discussion of policy implications, and a conclusion. The section also identifies avenues for future research.

2. LITERATURE REVIEW

The forecasting of future stock price movements has consistently attracted significant interest from both researchers and investors. The inherent complexity of this endeavor stems from the diverse and extensive range of influential factors and information sources that must be considered, rendering precise prediction of future stock market behavior exceptionally challenging. Despite the acknowledged difficulty in accurately predicting stock prices, a substantial body of research continues to explore various methodologies aimed at addressing this challenge (Brown et al., 1998).

The inherent complexity and unpredictability of the stock market have consistently made the predictability of stock returns a focal point of extensive research. This debate is largely shaped by Fama's (1970) efficient market hypothesis, which posits that current asset prices fully reflect all available information, and the random walk hypothesis, asserting that stock price changes are independent of past movements (Burton, 2018). Consequently, these hypotheses collectively suggest the absence of reliable methods for accurate stock price prediction. Despite the acknowledged difficulty in accurately predicting stock prices, a substantial body of research continues to explore various methodologies aimed at addressing this challenge.

The application of machine learning (ML) techniques to forecast stock market movements has gained significant traction in recent financial literature, driven by the potential for improved prediction accuracy over traditional econometric models, especially given the complex and often non-linear nature of financial time series. Researchers globally have explored various algorithms to predict future asset prices. For instance, Krauss et al. (2017) provided a comparative analysis on the S&P 500 index, evaluating the predictive power of deep neural networks (DNN), gradient-boosted trees, random forests (RF), and ensemble combinations thereof, demonstrating the potential of sophisticated ML methods in mature markets. Osama et al. (2024) conducted a comparative study evaluating Long Short-Term Memory (LSTM), Random Forest, Support Vector Regression (SVR), and Linear Regression for predicting Oracle stock prices, identifying SVR as the best-performing model with LSTM also performing well, while Random Forest showed poor performance. Bansal et al. (2022) also conducted a comprehensive study comparing five algorithms, including K-Nearest Neighbors, Linear Regression, Support Vector Regression, Decision Tree Regression, and Long Short-Term Memory, for predicting stock prices of 12 leading Indian companies, concluding that the LSTM deep learning algorithm consistently outperformed the others.

Within the Turkish context, numerous studies have adapted these advanced computational methods to predict local market dynamics. Several researchers have compared the efficacy of different ML algorithms. Ustalı et al. (2021) focused on predicting stock prices within the XU 30 index using Artificial Neural Networks (ANN), RF, and Extreme Gradient Boosting (XGBoost), concluding that XGBoost yielded the best performance (72.2% accuracy), followed closely by RF (69.5%), with ANN lagging slightly (68.6%). Similarly, Egüz et al. (2022) specifically targeted Turkish bank stocks, comparing linear regression, lasso regression, Support Vector Machines (SVM), decision trees, RF, and XGBoost. Their findings also highlighted XGBoost as the superior algorithm for predicting bank stock prices in Türkiye. In another comparative study, Doğan and Büyükkör (2022) applied Support Vector Regression (SVR), RF, and XGBoost to predict indices and high-volume stocks on the Borsa Istanbul, identifying SVR as the most effective method in their specific application. Toprak et al. (2022) focused on predicting the stock price of Petkim Petrokimya Holding Corp. (PETKM) on Borsa Istanbul, utilizing its stock price, the USD/TRY exchange rate, and the BIST Chemical, Petroleum & Plastic (XKMYA) index price as inputs; their study employed Random Forest Regression (RFR), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN), finding LSTM and RFR models to outperform CNN with MSE values below 0.02, while all three algorithms demonstrated strong predictive capabilities with R2 values exceeding 95%. Karaca and Dökmen (2024) forecasted daily closing prices for the top 5 highest market value stocks traded in BIST 100 between 2016 and 2020, applying multiple linear regression, Bayesian regression, random forest, decision trees, support vector machines, and artificial neural networks, and found artificial neural networks to yield the most successful results. These studies collectively indicate the strong potential of ensemble methods like XGBoost and kernel

methods like SVR for Turkish market prediction, though the optimal choice may depend on the specific asset and timeframe.

These studies collectively indicate the strong potential of ensemble methods like XGBoost and kernel methods like SVR for Turkish market prediction, though the optimal choice may depend on the specific asset and timeframe.

Beyond these comparative analyses, deep learning approaches have also been prominently featured in recent Turkish financial forecasting literature. Dalkıran and Ozan (2022) specifically employed deep learning techniques to forecast the daily closing prices of a major Turkish bank's stock (ISCTR), which is a component of the BIST Banking Index. Extending the focus to broader market indicators, Akbulut and Adem (2023) successfully utilized Long Short-Term Memory (LSTM) models, a type of recurrent neural network (RNN), to predict the Borsa Istanbul index. Further exploring deep learning capabilities, Pamukçu et al. (2023) applied both RNN and LSTM algorithms to predict daily values for the US Dollar exchange rate, Gold prices, and the BIST 100 index, with their results strongly favoring LSTM. Phuoc et al. (2024) aimed to predict stock price trends in an emerging economy's stock market using the LSTM algorithm along with technical analysis indicators and secondary data from VN-Index and VN-30 stocks, demonstrating high accuracy and affirming LSTM's suitability for stock price movement analysis and forecasting. Teixeira and Barbosa (2025) analyzed stock price forecasting focusing on time series models and deep learning techniques, including RNN, LSTM, GRU, CNN, and XGBoost, and found that complex models like XGBoost and GRU were particularly effective in capturing patterns and making accurate predictions in intricate stock price time series.

Stock price prediction using machine learning (ML) is a high-stakes and deeply researched application of data science, aimed at forecasting future prices of stocks using historical data and auxiliary inputs. Unlike traditional statistical methods (like ARIMA), ML approaches aim to capture non-linear patterns, hidden dependencies, and regime shifts often missed by classical models. However, stock markets are inherently noisy, non-stationary, and influenced by unpredictable external events making prediction both complex and risky. ML methods provide probabilistic edges, not certainties. The reviewed literature highlights the successful application of various machine learning methodologies to forecast components of the Turkish financial market, such as individual stocks, specific bank shares (like ISCTR), and general market indices (like BIST 100 and XU 30). These studies effectively demonstrate the potential of ML techniques in capturing the complex dynamics of financial assets in Türkiye. Building upon this foundation, the present study seeks to contribute by specifically focusing on the BIST Bank Index (XBANK) itself, a critical barometer of the nation's financial health. While previous research has touched upon bank stocks or broader indices, this work undertakes a dedicated analysis predicting the XBANK index using macroeconomic and financial indicators over an extensive 20-year period (2004-2024) and comparing the performance of contemporary machine learning, including ensemble, methods. Therefore, this study contributes to the existing body of work by providing a focused, long-term forecast for the XBANK index, aiming to generate accurate predictions which, in turn, can offer valuable insights for risk assessment and potentially inform policy considerations regarding financial stability in Türkiye.

3. DATA

The dataset utilized in this study comprises monthly data spanning from 2004 to 2024. Table 1 provides details on the data sources and explanations for the macroeconomic and financial

indicators employed to estimate the XBANK index. The selection of these variables is firmly rooted in established macroeconomic and finance literature, which consistently underscores their significant influence on stock market movements. While traditional studies often examine linear relationships, the chosen macroeconomic and financial variables are widely recognized for their effectiveness in forecasting stock prices and for providing meaningful insights into market dynamics. These variables were selected because they represent key factors influencing the broader economic environment and financial conditions within which banks operate. For instance, macroeconomic indicators related to economic activity and price levels can affect loan demand and credit quality, while financial indicators such as interest rates and exchange rates directly impact bank profitability and balance sheet valuations. Therefore, changes in these indicators are expected to have predictive power for the performance of the BIST Bank Index.

Variables	Data Source	Definition
XBANK	CBRT - EVDS	BIST Bank Index
currency	CBRT - EVDS	Currency USD/TL
CPI	CBRT - EVDS	Consumer Price Index
CCI	TÜİK	Consumer Confidence Index
CBRT_pol_rate	IMF-IFS	Central Bank Policy Rates
M2	CBRT - EVDS	Broad Money Growth (%)
CBRT_res	CBRT - EVDS	Central Bank Reserves
total_loans	CBRT - EVDS	Total Deposits Growth (%)
IPI	TÜİK	Industrial Production Index
CDS	Investing.com	Türkiye Credit Default Swap $
VIX	Investing.com	CBOE Volatility Index

Table 1. Explanations of Variables Used in the Study

4. METHODOLOGY

This study employs several machine learning regression algorithms to forecast the BIST Bank Index (XBANK) using the selected macroeconomic and financial indicators. The performance of these models is rigorously evaluated using standard statistical metrics.

4.1.Random Forest Regressor

Random Forest (RF) is a powerful ensemble machine learning algorithm widely used for regression tasks. It operates by constructing a multitude of decision trees during the training phase on various bootstrap samples of the dataset (bagging). Furthermore, RF enhances diversity among the trees by considering only a random subset of features when determining the best split at each node. The final prediction is obtained by averaging the predictions of all individual trees in the forest, which generally leads to improved accuracy and robustness against overfitting compared to single decision trees (Breiman, 2001).

4.2.XGBoost Regressor

Extreme Gradient Boosting (XGBoost) represents an optimized and highly efficient implementation of the gradient boosting framework, renowned for its predictive accuracy and computational speed. Like other boosting algorithms, XGBoost builds models sequentially, where each new tree attempts to correct the errors made by the ensemble of previously trained

trees. It incorporates several advanced features, including regularization (L1 and L2 penalties) to mitigate overfitting, built-in procedures for handling missing values, and optimizations for parallel processing (Chen and Guestrin, 2016). These characteristics make XGBoost a popular choice for complex regression problems in finance.

XGBoost is particularly effective in handling high-dimensional data and allows for automatic handling of missing values. Furthermore, its regularization capabilities make it suitable for financial time series that exhibit nonstationarity and volatility. Despite its complexity, the model's internal structure allows for feature importance extraction, which was leveraged to support the interpretation of model outputs.

4.3.Gradient Boosted Regression Trees (GBRT)

Gradient Boosting (GBRT) is another influential ensemble technique that constructs a predictive model iteratively, typically using decision trees as base learners. The core idea is to build models sequentially in a stage-wise fashion, where each new model focuses on minimizing the loss function (e.g., mean squared error) by fitting to the residual errors (the negative gradient) of the preceding ensemble (Friedman, 2001). This additive training process allows the model to progressively improve its predictions by correcting past mistakes. While powerful, GBRT models can sometimes require careful tuning of hyperparameters to prevent overfitting. One of the main advantages of GBRT is its high predictive accuracy, especially in cases where the underlying data-generating process is complex and non-additive. The model also provides insights into variable significance through its built-in feature importance mechanism, which was applied to assess the contribution of each macroeconomic variable to the XBANK index forecast.

4.4.Statistical Analysis

The evaluation of the prediction performance of the models was conducted by utilizing the mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) evaluation criteria. MAE measures the average absolute difference between the predicted and actual values, providing an easily interpretable measure of average error magnitude. RMSE calculates the square root of the average of squared errors, penalizing larger errors more heavily and giving a sense of the typical error size in the units of the target variable. The R^2 score indicates the proportion of the variance in the dependent variable (XBANK index) that is predictable from the independent variables, serving as a measure of the model's goodness of fit, with values closer to 1 indicating a better fit.

The evaluation of the prediction performance of the models was conducted by utilising the mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination evaluation criteria (R^2) in equations (1)-(3), respectively.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} |\bar{\mathrm{y}}_{\mathrm{i}} - \mathrm{y}_{\mathrm{i}}| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\bar{\mathrm{y}}_{\mathrm{i}} - \mathrm{y}_{\mathrm{i}})^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}{\sum_{i=1}^{n} (y_i - \hat{y})^2} \tag{3}$$

where, $\bar{\mathrm{y}}_{\mathrm{i}}$ is the i-th predicted value; y_i is the actual value of the ith sample, and $\hat{\mathrm{y}}$ is the mean of the y values; n represents the total number of samples.

5. EMPIRICAL RESULTS

5.1.LazyRegressor

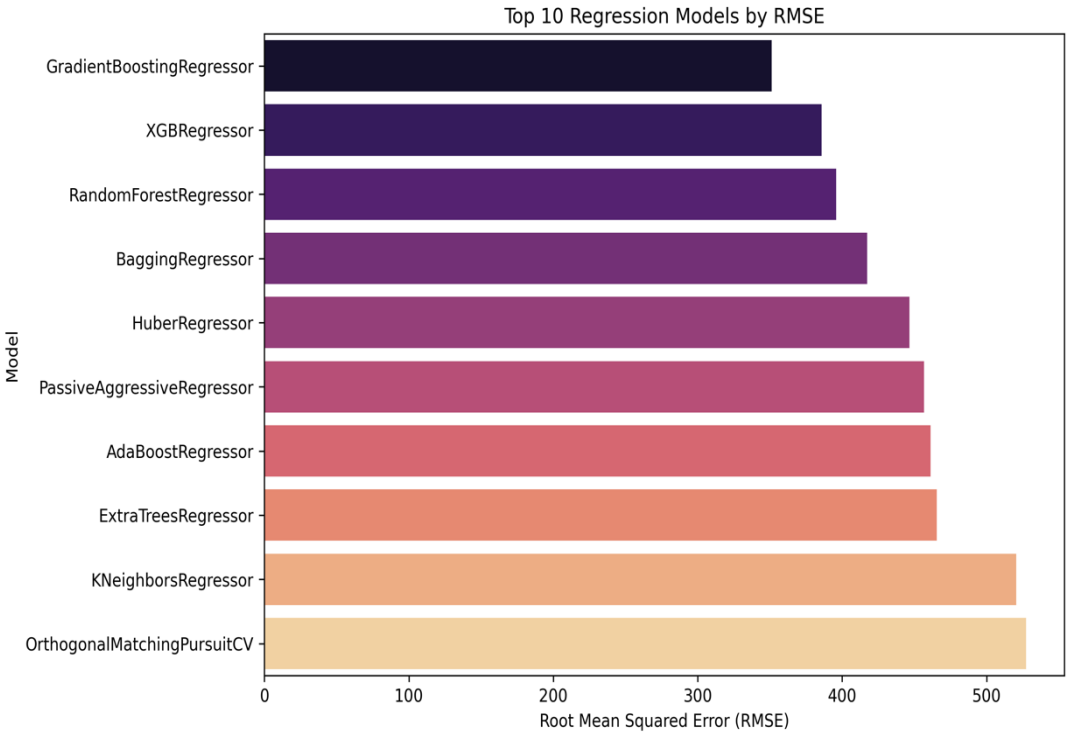
In the preliminary analysis conducted using the LazyRegressor library, 42 different regression algorithms were systematically tested on the dataset used in the study. In this analysis, the performance of each model was compared based on standard regression evaluation metrics, such as R^2 score, RMSE, and processing time. Following a thorough investigation into available models, it was determined that the Gradient Boosting Regressor, XGBoost Regressor, and Random Forest Regressor models were the most effective, as evidenced by their high R^2 scores and low error rates. These models consistently yielded superior outcomes in comparison to competing models. Table 2, LazyRegressor analysis demonstrates that these three models exhibited optimal performance in terms of both R^2 score and RMSE values.

Model	Adjusted R-Squared	R-Squared	RMSE	Time Taken
GradientBoostingRegressor	0,9863	0,9891	351,2753	0,174
XGBRegressor	0,9835	0,9868	385,6235	0,4691
RandomForestRegressor	0,9826	0,9861	395,908	0,299

Table 2. LazyRegressor Results.

Figure 2 below provides a visual representation of the top 10 regression models in the LazyRegressor analysis, with the RMSE values used as a metric for model comparison. A thorough examination of the graph reveals that the Gradient Boosting Regressor model attained the lowest error value and exhibited optimal performance. The XGBRegressor and RandomForestRegressor models also demonstrate a high level of accuracy, with similarly low Root Mean Square Error (RMSE) values. These findings indicate that the subsequent stages of the study should entail the subjection of these three models to hyperparameter optimization, a choice that is methodologically sound.

Figure 2. LazyRegressor Results for XBANK Prediction



Source: Author's own work.

Consequently, the analysis led to the selection of only the three models demonstrating optimal performance for the subsequent stages of the study, which entailed a detailed hyperparameter optimization process. Consequently, the selection of the model was grounded in statistical objectivity and methodologically reinforced by the LazyRegressor pre-screening.

5.2.Comparative Performance Analysis

This section presents the comparative performance evaluation of the Random Forest (RF), XGBoost, and Gradient Boosting (GBRT) models applied to predict the BIST Bank Index (XBANK). The performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2), derived from the application of these models, are detailed in Table 3.

Model	GradientBoosting	XGBoost	RandomForest
RMSE	366,1848	401,012	453,3414
MAE	184,4807	181,6867	257,1301
R2 Score	0,9881	0,9858	0,9818

Table 3. Model Performance Results.

Based on the evaluation results shown in Table 3, the Gradient Boosting model emerged as the most successful predictor overall. It achieved the lowest Root Mean Square Error (RMSE) of 366.18 and the highest coefficient of determination (R^2) value of 0.9881, indicating a strong fit to the data and relatively small prediction errors on average. Furthermore, its low standard deviation across cross-validation test folds (0.0035) suggests consistent and stable performance.

The XGBoost model also demonstrated strong predictive capability, performing comparably to Gradient Boosting. Notably, XGBoost achieved the lowest Mean Absolute Error (MAE) of

181.69, signifying that, on average, its individual predictions deviated the least from the actual values in absolute terms. Although its RMSE and R^2 were slightly less optimal than Gradient Boosting's, its strong MAE score positions it as a highly competitive alternative.

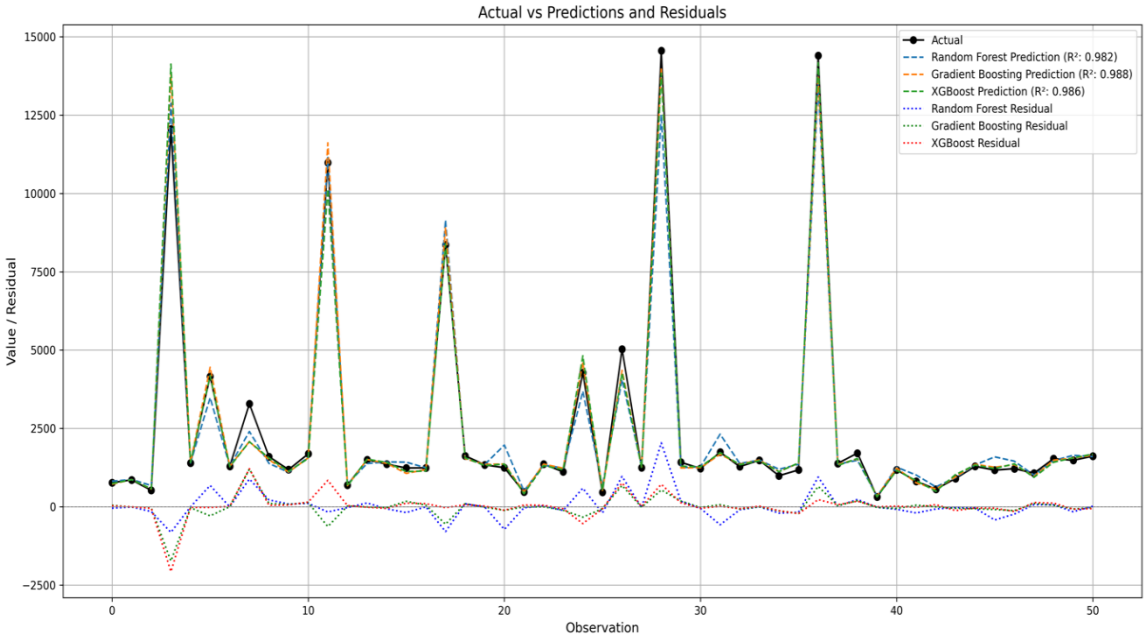
Conversely, the Random Forest model exhibited relatively weaker performance compared to the two boosting algorithms. It yielded higher error metrics, with an RMSE of 453.34 and an MAE of 257.13, and a lower average test R^2 score of 0.9470. These results suggest that, for this specific task of forecasting the XBANK index with the given features, the bagging approach of Random Forest was less effective than the sequential error-correcting approach of the boosting methods.
In summary, the comparative analysis highlights the superiority of the boosting algorithms for this forecasting problem. While XGBoost excelled in minimizing absolute errors (MAE), the Gradient Boosting model provided the best balance of low overall error (lowest RMSE), high explanatory power (highest R^2), and consistent performance, identifying it as the optimal model among those evaluated for predicting the XBANK index.

As illustrated in Figure 3, the figure displays the alterations in real XBANK values over time, in conjunction with the distribution of residuals produced by the Gradient Boosting model.

As demonstrated in Figure 3, the upper panel indicates that the model produces predictions that are in close proximity to the actual data, particularly during periods of rising or falling trends. The prediction curve successfully captures the general trend and closely matches the actual XBANK values. This finding lends further support to the Gradient Boosting algorithm's capacity to model strong non-linear relationships.

The residual graph in the lower panel demonstrates that the errors fluctuate around zero. The absence of a systematic pattern in the residuals over a specific time interval indicates that the model does not contain bias and that the homoscedasticity assumption (constant variance) is largely satisfied. However, it is important to note a few outliers. These points represent situations where the model has relatively more difficulty in predicting extreme values. Nevertheless, such deviations are to be expected in financial time series and do not significantly compromise the model's overall validity.

Figure 3. XBANK Actual Values and Predicted Values



Source: Author's own work.

This graphical analysis lends further support to the hypothesis that the Gradient Boosting model performs successfully in predicting the XBANK index, as evidenced by both statistical metrics and visual confirmation.

5.3. Policy Implications

The findings of this study, particularly the feature importance analysis presented in Table 4, offer significant insights for policymakers, financial regulators, and market participants concerned with the stability and performance of the banking sector in Türkiye. The relative importance assigned by the predictive models to various macroeconomic and financial indicators highlights key areas for policy focus.

As clearly indicated in Table 4, domestic macroeconomic factors dominate the prediction of the XBANK index. The Consumer Price Index (CPI) emerges as the single most critical variable (Importance: 0.3665), strongly suggesting that maintaining price stability is paramount for the health and valuation of the banking sector. This underscores the need for a monetary policy framework firmly anchored in controlling inflation to foster confidence and mitigate risks associated with deteriorating asset quality.

Variables	Importance
CPI	0,36652
CBRT_pol_rate	0,28572
CBRT_res	0,12526
currency	0,06999
IPI	0,06169
CDS	0,02939
CCI	0,0243
VIX	0,02219
M2	0,00811
total_loans	0,00684

Table 4. Feature Importance for XBANK Index Prediction.

The CBRT policy interest rate ranks second in importance (Importance: 0.2857), emphasizing the direct impact of monetary policy decisions on the banking index. This finding reinforces the necessity for predictable and consistent interest rate management to stabilize market expectations and support financial sector performance. Closely related is the significant influence of CBRT foreign exchange reserves (Importance: 0.1253), highlighting the role of adequate reserves in bolstering confidence and providing a buffer against external volatility, which is crucial for financial stability.

Conversely, traditional monetary aggregates like M2 (Importance: 0.0081) and measures of credit like total domestic loans (Importance: 0.0068) show considerably lower importance in the model's predictions. This may suggest that for forecasting short-term banking index movements, direct policy levers (interest rates) and core macroeconomic outcomes (inflation) are more indicative than broader monetary supply or credit volume measures. Furthermore, the relatively modest importance of global risk indicators such as the VIX index (Importance: 0.0222) and CDS spreads (Importance: 0.0294) implies that while external factors play a role, domestic macroeconomic management and policy credibility appear to be more decisive drivers for the XBANK index according to the model.

In essence, these results advocate for a policy agenda prioritizing disciplined inflation control, consistent and transparent interest rate policies, and prudent management of foreign exchange reserves as key pillars for supporting banking sector stability and performance in Türkiye.

CONCLUSION AND FUTURE RESEARCH

This study aimed to forecast the BIST Bank Index (XBANK) in Türkiye for the period 2004-2024 using macroeconomic and financial indicators through a comparison of machine learning methods, specifically Random Forest, XGBoost, and Gradient Boosting. The application of these techniques, which overcome limitations of traditional econometric models by not requiring strict assumptions like linearity or normality, provided valuable insights into predicting this critical financial index. The following key results were obtained in this study: The comparative analysis demonstrated that ensemble machine learning models, particularly boosting algorithms, are highly effective for forecasting the XBANK index. GBRT emerged as the superior model, yielding the lowest Root Mean Squared Error (RMSE), the highest coefficient of determination (R^2), and demonstrating the most stable performance across validation folds after hyperparameter optimization via Grid Search. While XGBoost also

performed robustly, achieving the lowest Mean Absolute Error (MAE), GBRT offered the best overall balance of accuracy and consistency. Random Forest, while a powerful algorithm, showed relatively weaker performance for this specific task compared to the boosting methods. Furthermore, the feature importance analysis highlighted the dominance of domestic macroeconomic factors. Notably, the Consumer Price Index (CPI), the CBRT policy interest rate, and CBRT foreign exchange reserves were identified as the most influential predictors, underscoring the critical role of price stability, monetary policy, and reserve adequacy in shaping the banking sector's outlook in Türkiye. Indicators such as M2 money supply, total loans, and global risk metrics like the VIX index showed comparatively less predictive power within the models employed.

The findings of this study, particularly the high predictive accuracy achieved by the GradientBoosting model for the BIST Bank Index, align consistently with a growing body of literature demonstrating the superior performance of advanced machine learning techniques in financial forecasting. Several studies, both globally and within the Turkish context, have similarly highlighted the efficacy of ensemble methods and deep learning algorithms. For instance, Krauss et al. (2017) showed the potential of deep neural networks, gradient-boosted trees, and random forests for predicting the S&P 500. More specifically in Türkiye, Ustalı et al. (2021) found XGBoost to be highly effective for the XU 30 index, while Egüz et al. (2022) concluded that XGBoost also offered superior predictions for Turkish bank stocks. Furthermore, Toprak et al. (2022) achieved high R2 values using Random Forest Regression for a Turkish petrochemical stock, and Phuoc et al. (2024) demonstrated high accuracy with LSTM in an emerging market, reinforcing the robustness of these sophisticated models in capturing complex financial market dynamics. These consistent results underscore the significant utility of such models for accurate stock price forecasting.

These findings affirm the utility of advanced machine learning methods for financial forecasting; however, the study certainly has limitations that warrant consideration and open avenues for future research. Although the utilized dataset spanned two decades, the analysis was constrained by the specific set of available macro-financial indicators, potentially omitting relevant qualitative factors (e.g., political climate, regulatory changes) or granular banking sector metrics (e.g., non-performing loan ratios, capital adequacy). Furthermore, while the employed tree-based models inherently handle non-linearities, explicit time-series structures like lagged variables or rolling window approaches were not formally incorporated, which might enhance predictive accuracy for temporally dependent data. The model evaluation relied on standard performance metrics (RMSE, MAE, R^2), and future work could benefit from incorporating formal statistical significance testing and robustness checks, such as out-of-sample validation across distinct economic regimes or structural breaks. Additionally, this study focused on comparing specific ensemble models; exploring hybrid frameworks that combine machine learning with traditional econometric methods or deep learning architectures like Long Short-Term Memory (LSTM) networks could potentially yield synergistic benefits and capture different facets of the time series dynamics. Finally, the results are inherently specific to the Turkish banking sector and the examined period. Expanding the scope to include cross-country comparisons or analyses of different market segments could provide broader insights and test the generalizability of the findings. Addressing these limitations in subsequent research will undoubtedly contribute to a more comprehensive understanding and improved forecasting of financial indices using advanced computational techniques.

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