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Comparative Forecasting Performance of ML Regression Models: Evidence from Borsa Istanbul

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ABSTRACT

Purpose - This study examines stock price forecasting using regression-based machine learning models by leveraging the daily closing prices of 10 companies traded on Borsa Istanbul (Borsa İstanbul) over the 2016–2025 period. The research aims to inform model selection in financial time series forecasting by comparing predictive performance across forecast horizons defined as short-term (≤60 trading days ahead), medium-term (61–180), and long-term (≥180).

Design/ methodology/approach - Five regression-based machine learning models were employed: Linear Regression, Bayesian Linear Regression, Decision Tree Regression, Neural Network Regression, and Poisson Regression. Data were split in chronological order (no shuffling). Models were trained using three training shares (80%, 90%, and 99%) and evaluated out-of-sample for each forecast horizon. Performance was assessed consistently across the manuscript using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE; reported as "error rate (%)"), minimum–maximum percentage error, and the coefficient of determination (R^2).

Findings - Results show that no single model dominates across all horizons. Neural Network Regression performs best for long-term forecasts, while Decision Tree Regression and Poisson Regression perform comparatively better in the medium term. For short-term forecasts, Decision Tree Regression delivers the lowest error. Linear and Bayesian Linear Regression exhibit relatively higher errors under short- and medium-term volatility.

Discussion - The findings indicate that forecasting performance depends on the investment horizon, the temporal structure of the series, and prevailing market conditions. By providing a comparative evaluation on long-span, recent Borsa Istanbul data, the study suggests that algorithm choice in investment strategies should be optimized jointly by forecast horizon and data characteristics.

1. Introduction

Financial markets constitute one of the most dynamic and intricate structures within global economic systems. Investors operating in these markets seek to anticipate future price movements by applying a wide range of analytical techniques. However, the rapid dissemination of information in today's globalized financial environment, coupled with heightened volatility and the growing influence of macroeconomic variables, has rendered traditional analytical and statistical methods increasingly inadequate. In this context, artificial intelligence (AI) and machine learning (ML)–based approaches have emerged as innovative and effective alternatives for modeling and forecasting financial time series.

Machine learning algorithms have attracted considerable scholarly and practical interest in the field of stock price prediction due to their capacity to identify complex, non-linear relationships within large datasets and to generate forecasts based on historical data. Unlike conventional econometric models—which generally rely on linear assumptions and parametric constraints—AI-based models can adaptively learn patterns from data, making them particularly suitable for environments characterized by uncertainty, noise, and high-dimensional relationships such as stock markets. As a result, the utilization of AI-driven regression and forecasting models in financial decision-making processes has expanded significantly in recent years.

The present study investigates the predictive performance of several regression-based machine learning models in estimating stock price movements of companies traded on Borsa Istanbul between 2016 and 2025. Using daily closing price data for ten selected firms, five distinct algorithms—Linear Regression, Bayesian Linear Regression, Decision Tree Regression, Neural Network Regression, and Poisson Regression—were

ETHICAL APPROVAL: This study used secondary data and does not require ethical committee approval.

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implemented and tested under varying training shares and forecast horizons (short, medium, and long term). Through this framework, the study seeks to identify which model families provide the most accurate and robust predictions across different investment timeframes.

The overarching objective of this research is twofold. First, it endeavors to assess the applicability and effectiveness of AI-based regression techniques within the context of the Turkish financial markets, thereby contributing empirical evidence to a literature that remains relatively limited in this domain. Second, it conducts a comprehensive comparative analysis of model performances under varying learning rates (80%, 90%, and 99%) and forecast horizons, offering insights into how data partitioning and model complexity influence predictive accuracy. In doing so, the study sheds light on critical issues such as overfitting, learning saturation and temporal sensitivity in financial time series modeling.

From a broader perspective, the study’s findings are expected to make both theoretical and practical contributions to the field of financial econometrics. Theoretically, the research enhances the understanding of how AI-based regression algorithms can be systematically optimized for financial forecasting tasks. Practically, it provides valuable guidance for investors, analysts, and policymakers by identifying the specific market conditions and learning configurations under which these models yield superior predictive performance.

Ultimately, the research underscores that while AI-based regression models offer substantial potential in forecasting stock prices, no single algorithm consistently outperforms others across all conditions. Instead, model performance is contingent upon factors such as the data’s temporal structure, the learning ratio applied, and the forecasting horizon considered. Consequently, this study contributes to the growing body of interdisciplinary research that bridges financial analysis, machine learning and predictive modeling, providing an empirically grounded roadmap for the effective application of AI in financial markets.

2. Literature Review

Stock price prediction in financial markets has long been a significant research topic situated at the intersection of economics, finance, and artificial intelligence. However, most studies in the literature focus on a single machine learning algorithm or a limited dataset and do not sufficiently consider differences in investment horizons. In this study, using daily closing prices of 10 firms traded on Borsa Istanbul during 2016–2025, the short-, medium-, and long-term forecasting performances of five regression-based machine learning algorithms—Linear Regression, Bayesian Linear Regression, Decision Tree Regression, Neural Network Regression, and Poisson Regression—were comparatively analyzed. This approach addresses a common limitation in the literature by providing evidence that no single algorithm consistently outperforms others under all conditions.

Beyond traditional statistical techniques, it has been observed—particularly since the 2000s—that machine learning and artificial intelligence-based algorithms have significantly improved financial forecasting accuracy. Studies employing AI methods through regression-based algorithms for stock price prediction are presented in Tablo 1 below.

Tablo 1. Studies on Stock Price Prediction Using Artificial İntelligence-based Methods

AUTHOR(s)	YEAR	METHOD(S)	SUMMARY
Şıklar	1999	Bayesian Theorem	Demonstrated the use of Bayesian theorem for parameter selection in regression analysis. Provided a theoretical explanation of simple and multiple Bayesian linear regression models.
Altay and Satman	January 2005	Artificial Neural Networks (ANN), Linear Regression	Compared ANN and linear regression in predicting stock prices in an emerging market (Turkey). Found that ANN achieved higher predictive accuracy.
Deniz	June 2005	Poisson Regression Analysis	Highlighted the broad applicability of Poisson regression in modeling count data in fields such as health sciences, insurance, transportation, and economics. Concluded that Poisson

			regression provides more reliable results than traditional linear models when count data characteristics are present.
Chen, Shih and Wu	2006	Support Vector Machines (SVM), Back Propagation Neural Networks (BPNN)	According to the empirical analysis, the study investigated the performance disparities between two artificial intelligence-based methods—Support Vector Machines (SVM) and Back Propagation Neural Networks (BPNN)—in predicting the closing values of six major Asian stock markets. The predictive outcomes of these models were evaluated in comparison with traditional statistical approaches, with a particular focus on their applicability to the Asian financial context. The results indicate that the utilization of advanced machine learning models such as SVM and BPNN offers significant advantages in forecasting highly volatile financial markets like those in Asia, where conventional statistical techniques often exhibit limited predictive capability.
Tsai and Wang	March 2009	SVM, ANN, Decision Tree Regression, K-means Clustering	It was determined that the hybrid modeling approach provides higher predictive performance compared to individual machine learning models. The study emphasizes the effectiveness of hybrid machine learning methods in processing complex data structures in financial markets.
Atsalakis and Valavanis	April 2009	Fuzzy Logic, Artificial Neural Networks – ANN, Genetic Algorithms–GA, Neuro-fuzzy Models, Support Vector Machines–SVM	The study highlights that due to the high uncertainty and nonlinear nature of financial time series, traditional statistical techniques may be inadequate. The analysis of stock return forecasting revealed that machine learning techniques outperform conventional models in predictive accuracy.
Krollner, Vanstone and Finnie	April 2010	ANN, SVM, Genetic Algorithms, Decision Tree Regression, Reinforcement Learning, Particle Swarm Optimization, Ensemble Methods	The study underscores that traditional statistical approaches achieve limited success in the presence of high volatility, nonlinear dynamics, and uncertainty in financial market data. It was particularly found that artificial neural networks and hybrid approaches stand out in enhancing the accuracy of financial forecasting.
Tsai and Hsiao	December 2010	ANN, SVM, Decision Tree Regression	The findings indicate that the hybrid modeling approach provides superior predictive performance compared to individual machine learning models.
Shen, Jiang and Zhang	2012	SVM, ANN, Naïve Bayes, Decision Tree Regression, K-Nearest Neighbors (KNN)	It was identified that Support Vector Machines (SVM) and Artificial Neural Networks (ANN) deliver higher predictive accuracy relative to other methods. The study demonstrates that machine learning can serve as an effective tool for financial market forecasting while also

			noting that market fluctuations and nonlinear factors may constrain model performance.
Dondurmacı and Çınar	2014	Decision Tree Regression, ANN, Apriori Algorithm	The research demonstrates that data mining techniques can yield successful results on financial datasets and serve as effective analytical tools, particularly in customer segmentation, credit risk analysis, and the formulation of marketing strategies. The study emphasizes that data-driven decision-making processes provide a competitive advantage within the financial sector.
Abe and Nakayama	2018	Deep Neural Networks (DNN), LASSO, Ridge Regression	The model tested on cross-sectional stock data based on various firm characteristics achieved higher predictive accuracy compared to traditional regression models. The study concludes that deep learning exhibits promising potential in financial asset pricing and portfolio management.
Rasekhschaffe and Jones	May 2019	OLS Regression, Decision Tree Regression, Gradient Boosting Machines (GBM)	In the study, stock returns were predicted using firm-based financial factors and compared with traditional factor models. The findings reveal that machine learning approaches can enhance portfolio performance, emphasizing their value as a significant alternative for financial asset selection.
Zhong and Enke	December 2019	ANN, SVM	It was determined that hybrid models based on Principal Component Analysis (PCA) yield higher accuracy compared to models employing only ANN or SVM. The study demonstrates the effectiveness of technical analysis-based machine learning strategies by presenting a substantial improvement in market direction forecasting.
Karacan and Kırdar	February 2021	ANN, SVM, Decision Tree Regression	The study constructed models based on firm and financial indicators and compared traditional regression analyses with ANN, SVM, and decision tree methods. The results indicate that, unlike linear models, artificial intelligence and machine learning approaches exhibit superior performance in predicting stock prices.
Arda and Küçükkocaoğlu	August 2021	Linear Regression, Bayesian Linear Regression, Neural Network Regression, Poisson Regression, Decision Tree Regression	The study examined the effectiveness of artificial intelligence methods in predicting the stock prices of companies listed in Turkey's BIST 30 Index. The results indicate that neural network and Poisson regression methods were found to be more effective in estimating closing prices.
Ünvan and Ergenç	2022	Decision Tree Regression	The study compared the performance of artificial neural networks and regression analysis in forecasting the future values of the BIST 100 Index. The results revealed that artificial neural networks demonstrated higher

			predictive performance compared to regression models.
Songün and Akbalık	2023	Decision Tree Regression	Within the scope of the study, two different future time horizons were forecasted for each stock, and predictive models were developed using the decision tree algorithm. The results indicate that such artificial intelligence-based models can serve as effective tools for stock price prediction, particularly in financial time series characterized by nonlinear relationships, where they offer advantages over traditional models.

Overall, the literature demonstrates that no single model consistently outperforms others under all circumstances; model success varies depending on learning duration, data density, market volatility, and temporal factors. Accordingly, obtaining short-, medium-, and long-term forecasts at different learning rates, as in this study, is crucial for testing the real-world applicability of models.

Regarding this study's contribution to the literature, its originality lies not only in the diversity of algorithms but also in its inclusion of multiple investment horizons. Separate evaluations for short-, medium-, and long-term predictions reveal the impact of investment duration on model performance. Neural network regression showed superior performance in long-term forecasts, Poisson and decision tree regression performed better in the medium term, and decision tree regression achieved the best results in the short term. These findings highlight the importance of model selection based on investment horizon in financial time series forecasting.

Moreover, the dataset used in this study is both extensive and up to date, encompassing economic crises and post-pandemic market dynamics. Therefore, the study provides an opportunity to analyze how varying market conditions affect model performance. Focusing on the Turkish capital market adds a unique contribution to the literature, as long-span, firm-level data from Borsa Istanbul are particularly valuable for investors and researchers in emerging markets.

In performance evaluation, both error rates and the coefficient of determination (R^2) were utilized to comprehensively assess model accuracy. Furthermore, the results were interpreted in the context of short-, medium-, and long-term investment strategies, offering concrete insights for the effective use of AI-based models in financial decision-making processes.

In conclusion, this study distinguishes itself from existing literature through its methodological diversity and comprehensive dataset, providing original findings and practical recommendations for investment strategies in the Turkish financial market. It also serves as a foundational reference for future research integrating more complex ensemble learning methods and deep learning architectures.

2. Dataset and Methodology

In this study, the daily closing prices of 10 actively traded companies on Borsa Istanbul were used, covering the period from January 2, 2016, to June 8, 2025. The sample was constructed based on data continuity over the full period and active trading; therefore, it is not restricted to companies that are constituents of the BIST 30 at all times. Five regression-based machine learning models were implemented: Linear Regression, Bayesian Linear Regression, Decision Tree Regression, Neural Network Regression, and Poisson Regression. Poisson Regression is included as a generalized linear model benchmark (log-link on strictly positive prices), motivated by its use in prior applications and to test whether a distribution-linked specification improves robustness; its theoretical limitations for continuous price series are discussed in the findings. For each model, forecasts were produced and compared with realized closing prices.

Tablo 2. Firms Examined in This Research (2016–2025)

Stock Code	Number of Data
AGHOL	4678
AKYHO	4679
ALARKO	4675
AVHOL	4679
BYART	4678
ECZYT	4684
IHLAS	4674
INVEO	4684
KCHOL	4675
UNLU	4673
TOPLAM	46779

The dataset comprises daily closing prices for the 10 selected companies. The number of observations for each stock corresponds to trading days within 2016–2025 and reflects both market activity and data continuity. Minor differences in counts arise from holidays, temporary trading halts, and missing observations.

The size and continuity of the dataset are critical for training and evaluation in time-series forecasting. In order to enable the models to learn from past information while preserving the temporal ordering, a univariate feature set was constructed from lagged closing prices. Specifically, for each day t, the input vector consists of the previous p closing prices (lags) and the target is the closing price at t+k, where k corresponds to the selected forecast horizon. Prior to model training, the inputs were scaled using statistics computed on the training set only, to avoid information leakage.

In the analysis, the five regression-based models were trained under three different training shares (80%, 90%, and 99%). For each share, the split was performed chronologically so that earlier observations form the training set and later observations form the test set. This design makes the train/test split distinct from the forecast horizon: the training share controls how much history the model sees, while the horizon k controls how far ahead the prediction is made.

To prevent data leakage common in random splits of time series, no random sampling was used. Model performance was evaluated using a walk-forward (rolling-origin) procedure on the test segment: predictions were generated sequentially, and the evaluation aggregates errors over the full test interval. Forecast horizons were defined as short-term ($k \leq 60$ trading days), medium-term ($61 \leq k \leq 180$), and long-term ($k \geq 180$).

Model performance was evaluated using multiple metrics. MAE measures the average absolute deviation between predicted and realized prices. The "error rate (%)" reported in the tables corresponds to Mean Absolute Percentage Error (MAPE), computed as: $MAPE = (1/n)\cdot\Sigma \mid(y\_t - \hat{y}\_t)/y\_t\mid \cdot 100$. In addition, minimum and maximum percentage errors were reported to capture tail deviations, and R^2 was used as a measure of explained variance on the test data.

Overall, the methodology was designed to provide a transparent comparison of model families under different training shares and forecast horizons on Borsa Istanbul stock price series, with time-consistent splitting and explicitly defined evaluation metrics.

Ethics Committee Approval: Not required, as the study uses publicly available secondary market data and does not involve human participants, personal data, or animal subjects.

3. Findings

3.1. Long-Term Forecasts

For the long-term forecasts, the models were trained on the 2016–2025 series and used to generate out-of-sample forecasts for horizons of 180 trading days and longer in 2025. For clarity of presentation, Tables 3–5 and Figures 1–3 illustrate results for a representative stock; the same procedure was applied to all 10 companies, and the cross-horizon pattern is summarized in Şekil 4. In Tables 3–5, "Value" denotes the mean predicted closing price over the relevant test window.

Within the scope of the long-term forecasting analysis, the performance of the regression models was evaluated using both summary statistics and daily prediction–accuracy plots. The analysis focused on forecasts with a horizon of 180 days and beyond, where the models were trained with historical data and then used to produce forward-looking estimates. In this context, model stability and accuracy are of particular importance, given the inherent uncertainty associated with long-term forecasting conditions.

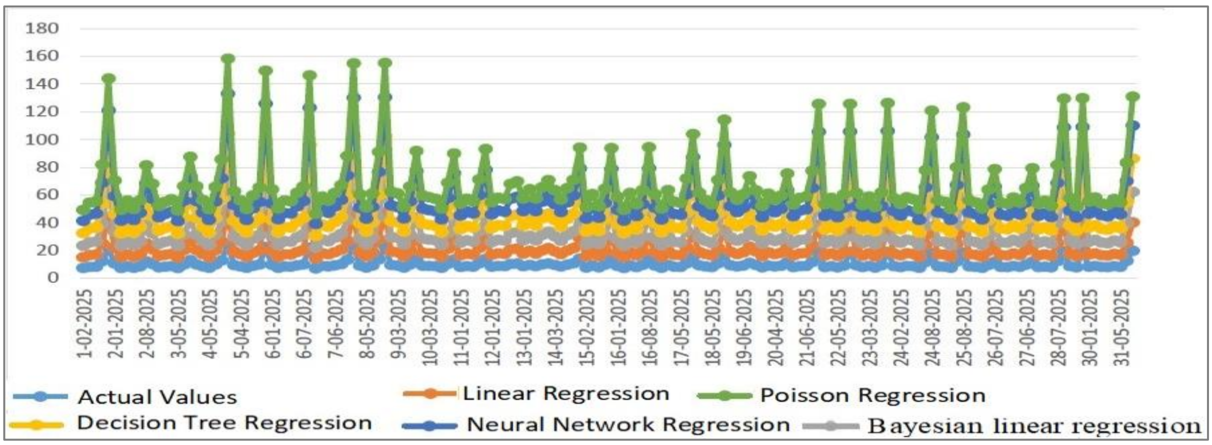
Tablo 3. Long-term Forecasts

	Predicted Value (Linear Regression)	**Predicted Value (Bayesian Linear Regression)**	**Predicted Value (Decision Tree Regression)**	**Predicted Value (Neural Network Regression)**	**Predicted Value (Poisson Regression)**
Value	195,2	202,4	204,3	193,9	195,5
Error Rate (%)	3,3	7,10	8,1	2,8	3,4
Minimum Error (%)	1,1	2,35	2,7	1,9	1,1
Maximum Error (%)	14,8	32,3	36,7	13	15,5
R^2	0,85	0,74	0,76	0,88	0,86

During the evaluated long-term test window, realized closing values fluctuated roughly between 183 and 194 TL, with an average around 189.5 TL. As reported in Tablo 3, Neural Network Regression achieved the lowest error rate (MAPE = 2.8%) and the highest R^2 (0.88). Linear Regression and Poisson Regression followed with similar accuracy (MAPE = 3.3% and 3.4%; R^2 = 0.85 and 0.86, respectively). Bayesian Linear Regression and Decision Tree Regression produced higher error rates (MAPE = 7.1% and 8.1%) and lower R^2 values (0.74 and 0.76).

Although the Bayesian Linear Regression and Decision Tree Regression methods provided consistent forecasting models in the long term, the observed error levels indicate that these models cannot serve as effective alternatives to the other approaches. The errors predicted by these models were approximately twice as high as those obtained from other models, leading to correspondingly lower R^2 values compared to the more robust models.

In the long run, while Linear Regression, Neural Network Regression, and Poisson Regression methods produced more effective results than the other two models, the Neural Network Regression method emerged as the most accurate model, with an average prediction error of 2.8%. A common feature among all three models was their tendency to produce predictions slightly higher than the actual observed values. On average, the predicted values did not fall below the actual nominal values. Although the prediction models were generally successful, the Neural Network Regression method can be regarded as the most suitable approach among them.



Şekil 1. Daily Analysis of Long-term Predictions

When the tabulated results and graphical analyses are evaluated together, it becomes evident that the Neural Network Regression model demonstrates superior performance compared to the other methods. With an error rate of 2.8% and an R^2 coefficient of 0.88, this model offers the lowest prediction error and the highest explanatory power. As shown in Şekil 1, the predictions generated by the Neural Network Regression model closely parallel the actual values and exhibit a high degree of sensitivity to fluctuations, indicating a strong alignment with real market movements.

Both Linear Regression and Poisson Regression also produced consistent results over the long term, yielding predicted averages close to the actual observed values. The Linear Regression model recorded an error rate of 3.3% and an R^2 value of 0.85, demonstrating its reliability in long-term forecasting despite its structural simplicity. Although the Poisson Regression model displayed occasional spikes in predictions during certain periods, its overall accuracy remained within an acceptable range.

On the other hand, the Bayesian Linear Regression and Decision Tree Regression models exhibited significantly higher error rates compared to the other models, with relatively lower R^2 values. As illustrated in Şekil 1, these models struggled to capture actual price movements accurately, systematically producing higher-than-expected forecasts and showing exaggerated reactions to volatility. Accordingly, it can be concluded that these two models fail to achieve sufficient stability for long-term forecasting purposes.

Overall, all models tended to overestimate the realized values, reflecting a generally conservative approach under long-term forecasting conditions. Nevertheless, based on both statistical metrics and graphical evaluations, the Neural Network Regression method stands out as the most suitable model for long-term forecasting. This result highlights that machine learning–based methods can outperform traditional linear models in long-term financial prediction tasks.

3.2. Medium-term Forecasts

In order to predict the medium-term closing values of the stock, various regression models were applied, and their performances were analyzed through both graphical and tabular evaluations. The results related to the medium-term forecasts identified in the second experiment are presented in Tablo 4.

Tablo 4. Medium-term Forecasts

	Predicted Value (Linear Regression)	**Predicted Value (Bayesian Linear Regression)**	**Predicted Value (Decision Tree Regression)**	**Predicted Value (Neural Network Regression)**	**Predicted Value (Poisson Regression)**
Value	104,8	110,1	98	108,1	100,2
Error Rate (%)	14	19,7	6,5	17,5	8,9
Minimum Error (%)	4,6	6,5	2,2	5,8	2,9
Maximum Error (%)	63,1	88,9	29,5	79,2	40,2
R^2	0,62	0,61	0,81	0,51	0,79

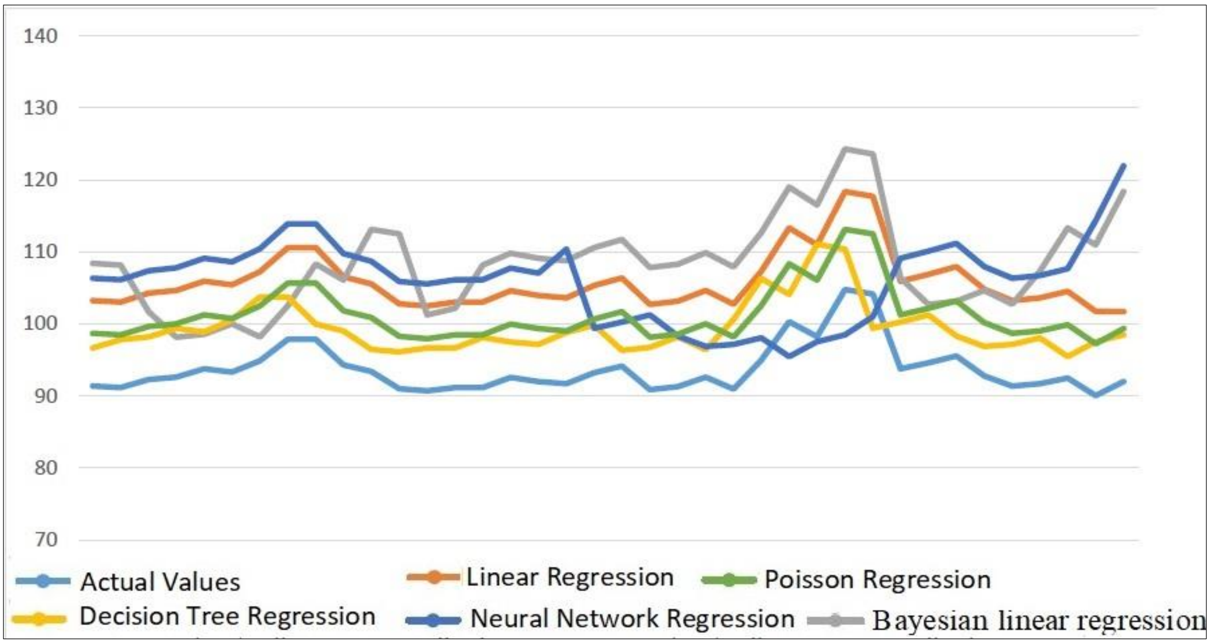
During the evaluated period, realized closing values ranged approximately between 98 and 126 TL, with notable jumps at specific dates, indicating a volatile regime that challenges medium-term forecasting. As shown in Tablo 4, Decision Tree Regression achieved the lowest average percentage error (MAPE = 6.5%) and the highest R^2 (0.81), indicating both strong fit and accuracy in this horizon. Poisson Regression followed with a lower error rate than linear models (MAPE = 8.9%) and a relatively high R^2 (0.79). Linear Regression and Bayesian Linear Regression exhibited higher error rates (14.0% and 19.7%, respectively) and lower explanatory power. Neural Network Regression underperformed in the medium term (MAPE = 17.5%, R^2 = 0.51), suggesting weaker generalization under this horizon and volatility profile.

According to Tablo 4, the lowest error rate (MAPE = 6.5%) was obtained from Decision Tree Regression. It also achieved the highest coefficient of determination (R^2 = 0.81), indicating the strongest explanatory power on the test data within the medium-term horizon. Poisson Regression also performed well (MAPE = 8.9%, R^2 =

0.79). In contrast, Linear Regression and Bayesian Linear Regression exhibited higher deviations with error rates of 14.0% and 19.7%, respectively. Neural Network Regression did not demonstrate the expected performance in the medium term (MAPE = 17.5%, R^2 = 0.51), suggesting weaker generalization under this horizon and volatility profile.

Among the models considered, linear regression, Bayesian linear regression, and neural network regression produced consistent forecasting behavior in the medium term; however, their overall performance cannot rival that of the other methods, as reflected in the error, minimum error, and maximum error levels. The forecasting errors for these models were approximately two to three times greater than those of the other algorithms. In the first experiment, the lowest error was 2.80% with the neural network regression algorithm, whereas in the second experiment, it was 6.5% with the decision tree regression. Another notable observation is that different algorithms performed best in the two experiments, suggesting that model efficiency depends heavily on the data horizon.

Overall, medium-term forecasting errors were higher than in the long-term analysis, reflecting greater sensitivity to local volatility and regime changes. Within this setting, the tree-based model's ability to capture nonlinearities appears advantageous, while the linear specifications remain limited in adapting to abrupt movements.



Şekil 2. Examination of Medium-term Forecasts

In Şekil 2, while the prediction lines of the linear models followed the trend of the actual values, they were unable to adapt to sharp fluctuations. In contrast, the decision tree and Poisson regression models tracked the price movements more closely and maintained lower forecasting errors. This indicates that during medium-term periods, price dynamics exhibit nonlinear characteristics, and traditional linear models may remain limited in capturing such patterns.

Additionally, it was observed that the error rates were relatively higher in medium-term forecasts compared to short- and long-term analyses. This can likely be attributed to the election process coinciding with the study period and the subsequent changes in economic policies, which led to fluctuations in investor behavior. Therefore, it can be inferred that during periods of policy-driven uncertainty, macroeconomic effects are reflected in market pricing more rapidly and irregularly.

In conclusion, although linear and Bayesian linear regression models produced consistent forecasts in the medium term, they lagged behind decision tree and Poisson regression models in terms of error levels and adaptability to volatility. The findings suggest that decision tree and Poisson regression methods offer superior forecasting performance in periods characterized by nonlinear data structures. Consequently, in medium-term forecasting studies, machine learning–based and distribution-sensitive methods are likely to yield more reliable results.

3.3. Short-Term Forecasts

In the third and final experiment, predictions were made for the last three-month period. This experiment, which has the shortest investment horizon, utilized the maximum learning duration. The results of short-term forecasts are presented in Tablo 5.

Tablo 5. Short-term Forecasts

	Predicted Value (Linear Regression)	Predicted Value (Bayesian Linear Regression)	Predicted Value (Decision Tree Regression)	Predicted Value (Neural Network Regression)	Predicted Value (Poisson Regression)
Value	64.5	65.9	62.1	67.5	64.4
Error Rate (%)	9.3	11.7	5.2	14.4	9.2
Minimum Error (%)	3.1	3.8	1.7	4.7	3
Maximum Error (%)	42	52.7	23.7	64.9	41.4
R^2	0.81	0.78	0.85	0.7	0.81

During the data period used, the estimated closing values of the stock ranged between 48 and 89 TL, with an average closing value of approximately 59.4 TL. When comparing the average error column, it is evident that the decision tree regression algorithm produced the most effective forecasts for this study.

According to the results in the table, the linear regression method yielded forecasts with a 9.3% error rate and a model strength of 0.81. The Bayesian linear regression method achieved forecasts with an 11.7% error rate and a model strength of 0.78. The decision tree regression method produced forecasts with a 5.2% error rate and a model strength of 0.85, while the Poisson regression achieved a 9.2% error rate and a model strength of 0.81.

Based on these findings, while linear regression, Bayesian linear regression, neural network regression, and Poisson regression produced consistent forecasts, their error rates indicate that they performed significantly worse than the decision tree regression method. The performance gap between the decision tree model and the other models reached 2–3 times in terms of average error rates.

In summary, the decision tree regression method demonstrated superior forecasting performance in the short term. However, the overall error levels in short-term forecasts were higher than those in long-term predictions. Considering the minimum and maximum error values, it can be concluded that the decision tree model predicted the price movements with high accuracy during the period.

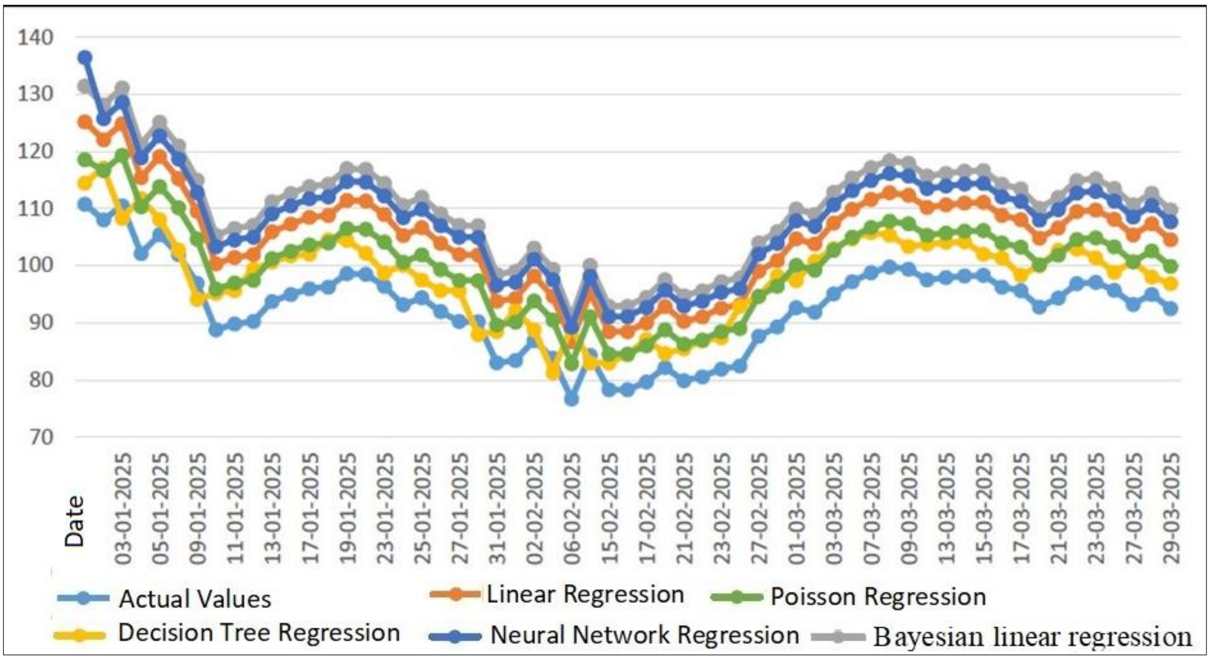
The short-term forecasting results reveal that the predictive performance of machine learning regression models in financial time series can vary significantly. Among the methods employed, the decision tree regression displayed by far the best performance. This can be explained by the structural characteristics of financial datasets: stock prices in the short term often exhibit high volatility, nonlinear dynamics, and abrupt market reactions. Given their strong capacity to model such nonlinear relationships, tree-based methods are expected to yield more effective results in short-term forecasting.

The relatively higher error rates of the linear and Bayesian linear regression models may stem from their inability to capture regime shifts, sudden trend reversals, and heteroskedastic structures, which are common in financial time series. Similarly, the unexpectedly higher errors of the neural network regression may indicate overfitting or an inability to fully abstract the data complexity during training. Moreover, as supported by the literature, neural networks require longer timeframes and larger datasets to perform effectively.

The Poisson regression, on the other hand, did not provide an ideal framework for modeling continuous price series, resulting in a performance level comparable to other linear methods. Although its explanatory power appeared reasonably satisfactory, the distributional characteristics of price movements render the Poisson model theoretically less suitable for financial variables.

In general, the higher error levels in short-term forecasts compared to long-term ones indicate that the short-term uncertainties and random components in financial markets cannot be fully captured by the models. This aligns with the concept of the "short-term forecasting paradox" in the literature, which denotes a structural phenomenon that weakens the predictive ability of models under micro-level market dynamics.

Consequently, the dominant performance of decision tree regression in the short term demonstrates that nonlinear modeling techniques can provide high effectiveness in financial series. Future research may combine more complex ensemble tree models (such as Random Forest, XGBoost, and LightGBM) with hybrid neural network approaches to enhance predictive accuracy. Additionally, incorporating volatility forecasts and market sentiment indicators into the models could substantially improve the forecasting performance for high-frequency short-term data.



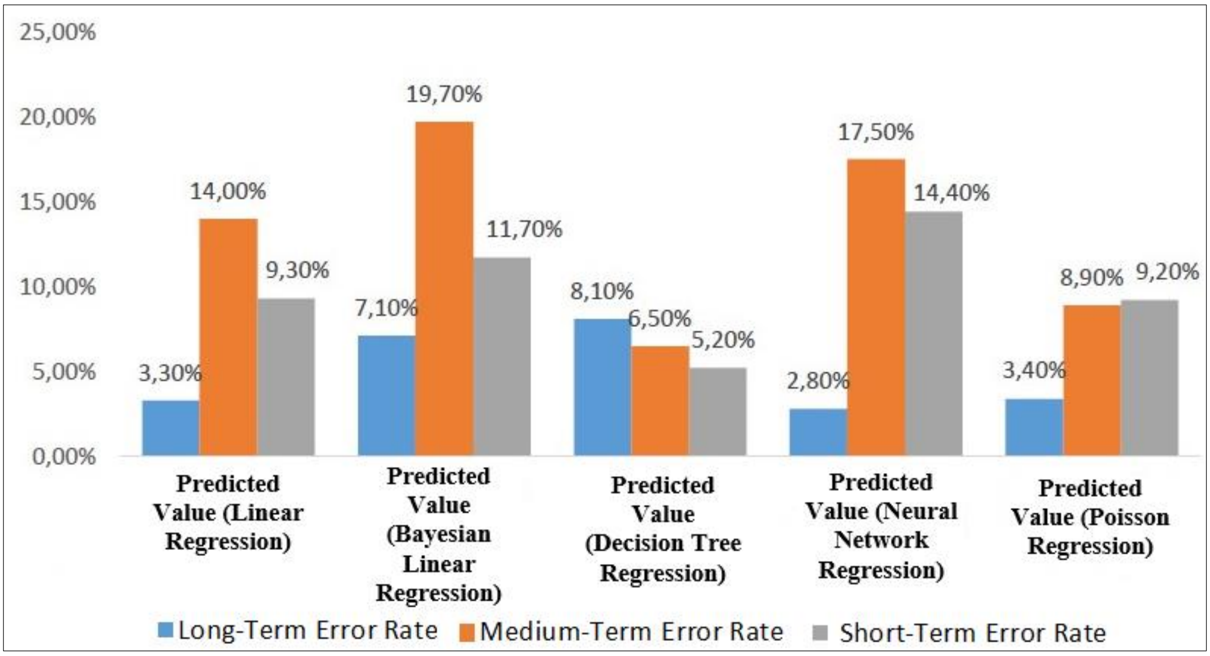
Şekil 3. Daily Analysis of Short-term Forecasts

As shown in Şekil 3, the actual closing values fluctuated throughout the period, with a notable decline in the first week of January, followed by short-term recovery movements. During this volatile period, which lasted from mid-January to early February, all models produced predictions close to actual values; however, the decision tree regression achieved the highest alignment with reality. Particularly during sharp price pullbacks (e.g., between late January and mid-February), the decision tree algorithm more accurately captured the downward movement compared to other models.

The neural network and Bayesian linear regression models, especially during periods of accelerated price fluctuations, were more prone to error, showing deviations either above or below actual values. This finding indicates that in short-term, high-volatility series, the neural network model may suffer from overfitting or insufficient generalization. Conversely, linear and Poisson regression models, while capable of following the general trend, demonstrated limited performance in capturing sudden price reversals, reflecting their lower adaptability to short-term market reactions.

Toward the second half of the period, particularly from March onward, a moderate recovery and a more sideways trend were observed in price levels. At this stage, the decision tree model maintained a high correlation with the actual values, while the other models remained within broader error bands. These results confirm that decision tree regression offers a systematic and stable advantage in capturing short-term market dynamics.

Overall, the figure demonstrates that the decision tree model more accurately captured both decline and recovery phases of market behavior, whereas other models exhibited larger error margins, particularly during volatile periods.



Şekil 4. Comparison of Error Rates by Period

As shown in Şekil 4, the lowest long-term error rate was achieved by Neural Network Regression, whereas Decision Tree Regression delivered the most effective and consistent performance in the medium and short terms. Poisson Regression produced balanced results across horizons, while Bayesian Linear Regression displayed the weakest performance due to comparatively high error and variance. Overall, the results indicate that model suitability is horizon-dependent: deep learning–based methods tend to be advantageous for longer horizons, while flexible nonlinear learners such as tree-based models are more effective for shorter horizons. Hybrid and ensemble strategies remain a promising direction for improving robustness across regimes.

4. Conclusion

In this study, five regression-based machine learning models were evaluated using daily closing prices (2016–2025) of ten companies traded on Borsa Istanbul. Models were trained under three chronological training shares (80%, 90%, and 99%) and assessed across short-, medium-, and long-term forecast horizons. For illustration, detailed tables and figures report results for a representative stock, while the comparative horizon-level conclusions hold across the full sample.

No single model consistently provides the most accurate forecasts under all conditions. Because distributional properties and temporal dynamics vary by horizon, performance differs across model families. The experiments also indicate that increasing the training share does not automatically improve forecasting accuracy; beyond a point, additional training can lead to learning saturation and overfitting, where the model begins to fit noise rather than persistent structure.

The findings reveal that financial time series can exhibit nonlinear structures across different periods, and consequently, no single model consistently outperforms others under all conditions. In long-term forecasts, the neural network regression achieved the lowest error rate (2.8%) and the highest R^2 value (0.88), demonstrating that wide datasets and long-term trend structures can be effectively learned by neural networks. The linear regression and Poisson regression also produced acceptable performance, whereas Bayesian linear regression and decision tree models performed relatively weakly in the long term.

In the medium term, the influence of market volatility and economic uncertainty became more pronounced, and the performance differences among models were more significant. The lowest error rate (6.5%) was observed in the decision tree regression, while the Poisson regression exhibited the highest explanatory power ($R^2 = 0.79$). The neural network regression did not meet expectations, and linear and Bayesian linear models showed limited predictive power under volatile conditions.

In the short term, the decision tree regression emerged as the most successful model (error rate 5.2%, $R^2 = 0.85$). The high volatility and nonlinear dynamics of short-term market movements made the tree-based methods more effective during this period. Conversely, linear models produced higher error levels, while Poisson and neural network models demonstrated moderate performance.

Overall, the study determined that the optimal model varies by investment horizon: neural network regression is more effective in the long term, Poisson and decision tree models in the medium term, and decision tree regression in the short term. These findings indicate that no single forecasting method is universally superior in financial time series analysis. The selection of the model should depend on the time horizon, data characteristics, and market conditions.

The results of this study are consistent with numerous findings in the literature, which also conclude that no single model dominates across all periods. The emphasis on the time-dependent structure of financial time series and the observation that different algorithms perform better over different horizons support the results of Bustos and Pomares (2019), who demonstrated that market volatility and structural breaks cause model performance to vary periodically and that hybrid or comparative modeling approaches tend to be more effective.

The observation that neural networks achieve higher accuracy in long-term forecasts is consistent with prior evidence that deep learning models can capture slow-moving trend structures when sufficient history is available (e.g., Abe & Nakayama, 2018; Songün & Akbalık, 2023). Conversely, the superior short-term performance of Decision Tree Regression aligns with the broader tree-based learning literature (e.g., Breiman, 2001), which highlights the ability of rule-based nonlinear models to adapt to local regime changes and volatility.

Future research could extend this comparative framework by incorporating additional model classes (e.g., Random Forest, Gradient Boosting, SVM, LSTM/GRU/Transformer) and by conducting systematic hyperparameter optimization. In addition, expanding the feature set beyond prices (e.g., volume, volatility proxies, interest and exchange rates, inflation, and sentiment indicators) may improve robustness. Finally, computational advances (including emerging hardware paradigms) may reduce training costs; however, such discussions are necessarily speculative and should be interpreted as forward-looking rather than as outcomes derived from the present empirical results.

While researchers and analysts aim to develop profitable trading strategies by successfully forecasting stock index values and stock prices, they also strive to design the least complex predictive models that use the fewest necessary input variables to achieve optimal results. In this study, the performance of several algorithms was measured across different learning durations. The time required to reach performance saturation was examined for each algorithm. Future studies may extend the analysis by incorporating different stock indices or alternative time horizons. The validity of the presented results can be tested using different methodologies, and the accuracy of models tailored to specific stock types can be improved accordingly.

In subsequent research, the scope can be broadened to include different indices or sectors. Incorporating additional Borsa Istanbul constituents (e.g., BIST 50 or BIST 100 companies) could enhance external validity and model validation. Furthermore, adding macro-financial indicators such as trading volume, volatility, interest rates, exchange rates, and inflation to the dataset could strengthen predictive power. Employing advanced deep learning architectures such as LSTM, GRU, Transformer, and Prophet could offer higher accuracy as alternatives to regression-based methods. In addition, applying hyperparameter optimization techniques (e.g., Grid Search, Random Search, Bayesian Optimization) and overfitting prevention strategies may further enhance algorithmic performance.

Future studies could also integrate external factors such as political developments, economic crises, or election periods into the models to predict market reactions more realistically. Moreover, the use of sentiment analysis derived from social media and news sources could contribute significantly to measuring the impact of investor behavior on prices. Finally, developing a real-time decision support system that dynamically presents daily forecasts to users could greatly expand the practical application of AI-driven financial analytics.

References

Abe, M., & Nakayama, H. (2018). Deep learning for forecasting stock returns in the cross-section. In D. Phung, V. Tseng, G. Webb, B. Ho, M. Ganji, & L. Rashidi (Eds.), Advances in knowledge discovery and data mining (PAKDD 2018) (Lecture Notes in Computer Science, Vol. 10937). Springer.

Altay, E., & Satman, M. H. (2005). Stock market forecasting: artificial neural network and linear regression comparison in an emerging market. Journal of Financial Management & Analysis, 18(2), 18.

Arda, E., & Küçükkocaoğlu, G. (2021). Yapay zeka yöntemleri ile hisse senedi fiyat öngörüleri. Ekonomi, Politika & Finans Araştırmaları Dergisi, 6(2), 565–586.

Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques — Part II: Soft computing methods. Expert Systems with Applications, 36(3), 5932–5941.

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.

Bustos, O., & Pomares-Quimbaya, A. (2020). Stock market movement forecast: A systematic review. *Expert Systems with Applications*, 156, 113464.

Chen, W. H., Shih, J. Y., & Wu, S. (2006). Comparison of support-vector machines and back propagation neural networks in forecasting the six major Asian stock markets. International Journal of Electronic Finance, 1(1), 49-67.

Deniz, Ö. (2005). Poisson regresyon analizi. İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi, 4(7), 59-72.

Dondurmacı, G. A., & Çınar, A. (2014). Finans sektöründe veri madenciliği uygulaması. Akademik Sosyal Araştırmalar Dergisi, 2(1), 258–271.

Karacan, S., & Kırdar, M. (2021). Hisse senedi fiyat tahmininde makine öğrenmesi ve yapay zeka kullanımı. Journal of International Social Research, 14(76), 666-681.

Krollner, B., Vanstone, B., & Finnie, G. (2010). Financial time series forecasting with machine learning techniques: A survey. Paper presented at the Proceedings of the 18th European Symposium on Artificial Neural Networks: Computational Intelligence and Machine Learning. Retrieved from https://pure.bond.edu.au/ws/files/27498056/Financial_time_series_forecasting_with_machine_learning_techniques.pdf

Rasekhschaffe, K. C., & Jones, R. C. (2019). Machine learning for stock selection. Financial Analysts Journal, 75(3), 70–88.

Shen, S., Jiang, H., & Zhang, T. (2012). Stock market forecasting using machine learning algorithms (Stanford University working paper). Stanford University. Retrieved from http://cs229.stanford.edu/proj2012/ShenJiangZhang-StockMarketForecastingusingMachineLearningAlgorithms.pdf

Songün, M. H., & Akbalık, M. (2023). BIST 30 endeksi paylarının yapay zeka yöntemleriyle tahmini üzerine bir araştırma. Finans Ekonomi ve Sosyal Araştırmalar Dergisi, 8(1), 270-286.

Şıklar, E. (1999). Regresyon analizinde Bayesçi yaklaşım. Anadolu Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 15(1), 113-122.

Tsai, C.F., & Wang, S.P. (2009) Stock price forecasting by hybrid machine learning techniques. Proceedings of the International Multi Conference of Engineers and Computer Scientists, 1, 60.

Tsai, C.F., & Hsiao, Y.C. (2010). Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. Decision Support Systems, 50(1), 258–269.

Ünvan, A. Y., & Ergenç, C. (2022). Forecasting BIST 100 index with artificial neural networks and regression analysis. BILTURK, The Journal of Economics and Related Studies, 4(1), 20–32.

Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation*, 5(1), 1–20.