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Çağdaş GÜNDÜZ

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Yapay Zekâ, Algoritmik Alım-Satım, Hisse Fiyatı Tahmini, Teknik Göstergeler, Borsa İstanbul.

ABSTRACT

This paper explores the performance of an artificial intelligence (AI)-based algorithmic trading system designed to predict stock price movements and generate trading signals in the Turkish stock market, Borsa İstanbul (BIST). The model integrates MACD, OTT, and MOST indicators and uses the FastForest algorithm, and was trained on 2,000 days of BIST Banking Index (XBANK) data. With 80% of data was allocated for training and 20% for validation, the system achieved over 79% directional accuracy in predicting buy, sell, and hold signals. In addition, comparative experiments with Random Forest and Support Vector Machine algorithms were conducted to assess robustness, confirming the consistency of the main model's performance. To reflect real market trading conditions, transaction costs ranging between 0.1% and 0.2% were incorporated into back testing scenarios. The strategy remained profitable even under cost-adjusted settings, demonstrating its practical viability. The results suggest that AI-driven systems can support retail investors by reducing costs and increasing trading efficiency. The model outperformed the XBANK index by generating total returns of 437.88% and 459.25% for Stock-1 and Stock-2 bank shares, respectively. These findings underscore the potential of AI-supported models in enhancing investment strategies in emerging and volatile markets.

ÖZ

Bu çalışma, Türkiye hisse senedi piyasası olan Borsa İstanbul (BIST) bünyesinde hisse senedi fiyat hareketlerini tahmin etmek ve alım-satım sinyalleri üretmek amacıyla tasarlanmış yapay zekâ (YZ) tabanlı bir algoritmik alım-satım sisteminin performansını incelemektedir. Model, MACD, OTT ve MOST göstergelerini bütünleştirmekte, FastForest algoritmasını kullanmaktadır. Çalışmada, BIST Bankacılık Endeksi'ne (XBANK) ait 2.000 günlük veri seti kullanılmış, verilerin %80'i eğitim, %20'si ise doğrulama amacıyla ayrılmış olup sistem, al, sat ve bekle sinyallerinin tahmininde %79'un üzerinde yönsel doğruluk elde etmiştir. Buna ek olarak, modelin sağlamlığını değerlendirmek amacıyla Random Forest ve Destek Vektör Makineleri (Support Vector Machine) algoritmalarıyla karşılaştırmalı deneyler gerçekleştirilmiş ve ana modelin performansının tutarlı olduğu doğrulanmıştır. Gerçek piyasa koşullarını yansıtmak amacıyla, %0,1 ile %0,2 arasında değişen işlem maliyetleri geriye dönük test (backtesting) senaryolarına dâhil edilmiştir. Maliyetler dikkate alındığında dahi stratejinin kârlılığını koruduğu gözlemlenmiş, bu durum modelin pratik uygulanabilirliğini ortaya koymuştur. Elde edilen bulgular, YZ destekli sistemlerin maliyetleri azaltarak ve işlem etkinliğini artırarak bireysel yatırımcıları destekleyebileceğine işaret etmektedir. Model, XBANK endeksini geride bırakarak Stock-1 ve Stock-2 banka hisseleri için sırasıyla %437,88 ve %459,25 toplam getiri sağlamıştır. Bu sonuçlar, YZ destekli modellerin gelişmekte olan ve dalgalı piyasalarda yatırım stratejilerinin etkinliğini artırma potansiyelini ortaya koymaktadır.

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INTRODUCTION

Potential revenues are the main motivation source for following the price changes in stock investments. Investors expect prices to increase and take a profit from the difference between buy and sell price. However, the structure of a stock market is very complex. Many internal and external factors lead to uncertainties in the market and these uncertainties make stock predictions more difficult. In this context, investors generally use fundamental analysis, where predictions are made by essentially examining the published financial statements of companies, and technical analysis, where predictions are made by analyzing historical prices and volumes to predict the stock trends together (Arslankaya & Toprak, 2021). Over the years, various methods have been developed for predicting stock market trends, but the accuracy and precision of most of them have been discussed for a long time. For this reason, stock price prediction has long been a major research focus, aiming to develop intelligent systems enabling more effective decisions in financial markets.

Some researchers have shown a preference for using only technical indicators, while others rely solely on historical data (Di Persio & Honchar, 2016; Qiu & Song, 2016). In recent years, artificial intelligence (AI) methods have also begun to be used in predicting future prices alongside traditional methods. AI has proven to produce more efficient solutions in nonlinear prediction problems, as it has the ability to select relevant information from historical data for making consistent predictions. The methods within AI vary in terms of memory structures, the number of layers that can be utilized, and their application domains (Gu et al., 2020; Vijh et al., 2020). Using various AI and machine learning (ML) approaches that assist investors in their investment decisions, better predictions for stock prices can be achieved. AI is a field dedicated to creating computer systems that mimic human intelligence and learning abilities, enabling machines to handle tasks like problem-solving, decision-making, language understanding, and visual recognition. ML, a subset of AI, focuses on creating algorithms that allow computers to complete tasks by recognizing patterns in data rather than relying on predefined instructions. While ML is part of AI, many AI applications go beyond the scope of ML (Uzunoğlu et al., 2024).

ML algorithms such as Gradient Boosted Regression Trees (GBRT), Ordinary Least Squares Regressions (OLS), The Least Absolute Shrinkage and Selection Operator (LASSO), Partial Least Squares (PLS), Elastic Net (ENET), Artificial Neural Networks (ANN), Support Vector Machine (SVM), Random Forests (RF), Tree-Based Conditional Sort (TBCS), Forecast Combination (COMB), Feed-Forward Neural Networks With One, Two, or Three Hidden Layers (NN1, NN2, NN3) can be used to predict trends in stock markets. While early approaches relied on classical regression techniques, the non-stationary nature of stock data has led to the adoption of nonlinear machine learning methods. Among these, TBCS, ANN and SVM are the most commonly employed algorithms for forecasting stock movements and price indices according to Wang et al. (2024) and Patel et al. (2015).

To Sakhare and Imambi (2019), there is no single algorithm that can predict stock market movements with absolute precision. Using limited features may hinder the predictive model's performance, while including all available financial market features can result in a complex and less interpretable model. Moreover, excessive variables might introduce collinearity, further degrading model performance (Bhandari et al., 2022). Therefore, many algorithms have been developed due to the critical need to accurately predict the direction of stock prices. Predicting the direction of stock prices correctly is the only way to profit from a trade. However, this critical need is not always present when using traditional forecasting methods. Investors target to foresee the trend of the price movement. Will it go up or down? How long will it last? When will the trend line begin to change its direction? Which markets will investors trade in? It is impossible to predict which news events will shape global markets. However, it is possible to determine the probabilities of price movements and achieve more precise results by using various AI algorithms.

Regarding the first three questions, one of fundamental aspects of understanding the direction of price movement is recognizing cycles and trends. Repeating cycles play a crucial role in shaping, directing, and influencing a trend line. For example, a series of upward-moving cycles, where each cycle's peak surpasses the previous one, ultimately

defines an upward trend. Over time, this causes the trend line to slope upward (Hooper et al., 2013). As for the fourth question, it should be noticed that every security market has unique characteristics influencing prediction methods. This research focuses on Borsa İstanbul (BIST) for three main reasons. First, BIST has experienced substantial growth in the number of listed companies and market size, drawing global interest from investors. Second, as a developing market, BIST faces gaps and fluctuations during its growth phase, with domestic investors playing a dominant role, contributing to higher trading volatility. Finally, recent government-driven reforms aim to reshape the market's structure, potentially offering new insights. These factors make the Turkish stock market a compelling case for re-examining return prediction challenges.

Considering the critical questions presented above, this paper utilizes an AI supported robotic trading system unifying various technical indicators, Moving Average Convergence/Divergence (MACD), Optimized Trend Tracker (OTT) and Moving Stop Loss (MOST) for addressing the return prediction issue in one of the rising emerging markets, the Turkish stock market. In addition, to ensure robustness and methodological reliability, the study performs comparative analyses with alternative ML algorithms (RF and SVM), incorporates resampling techniques to balance data, and evaluates model realism through cost adjusted back testing. As it is known, algorithmic trading (automated trading – AT) act on a strategy determined by the people using them and do not allow for human emotions. The acceleration of digitalization and technological advancements in financial markets has further emphasized the importance of AT. By enabling real-time data processing, fast and efficient trade execution, and reduced transaction costs, AT significantly influences investment strategies. The integration of AI and ML enhances decision-making processes, allowing for more sophisticated, data-driven approaches that benefit institutions and investors of all sizes in areas such as risk management and portfolio optimization. At this point, the paper targets to assist small investor group in facing with lower transaction costs, higher speed and higher liquidity by analyzing market data and identifying arbitrage opportunities quickly. It focuses on companies listing in the BIST Bank Index (XBANK).

The model we trained has been used a matrix-based infrastructure with AI support. During the training phase, various parameters (MACD, OTT, MOST) were employed as input to predict the stock value for the following day. A certain proportion of the relevant input was allocated for training (80%), while the remainder was used for validation (20%). Based on the obtained directional accuracy values, the system aims to generate buy, sell or hold commands for the stock. The system was developed using approximately 2,000 days in a daily period of BIST data as the dataset. In the study, FastForest model was elected as the training algorithm. The best results obtained were used to calculate profits, and these outcomes were shared. Following the completion of the training process, back test results demonstrate that the proposed AI model achieves satisfactory outcomes.

The study is expected to address the following gaps in the literature and provide the contributions outlined below.

Research gaps

1. While numerous studies such as Carta et al. (2021) and Khan et al. (2022) have focused on developed markets, there is limited research on AI-driven AT strategies tailored for BIST. The unique characteristics of BIST, such as its volatility and the dominance of domestic investors, present an opportunity for further exploration.
2. Most existing studies (Vaisla & Bhatt, 2010; Qiu & Song, 2016) either use a limited set of technical indicators or rely on fundamental analysis. However, integrating multiple technical indicators such as MACD, OTT, and MOST within an AI-driven robotic trading system remains an underexplored area.
3. While AI and ML have been extensively applied in hedge funds and institutional investment strategies, little attention has been given to how AI-based trading models can enhance decision-making for retail investors by lowering transaction costs and improving liquidity.
4. Most arbitrage-related AI research (Pun & Wong, 2019) has been conducted in highly liquid markets.

There is a need to investigate how AI-driven trading systems can efficiently identify and exploit arbitrage opportunities in markets with structural gaps like BIST.

Contributions to literature

1. Unlike previous studies that rely on single or limited indicators, this research integrates multiple technical indicators (MACD, OTT, MOST) within an AI-supported AT strategy, providing a more comprehensive approach to stock price prediction. It also analyzes whether selecting indicators from different categories yields more meaningful results for the companies listed in the XBANK.
2. By incorporating AI into arbitrage strategies, this study pioneers an approach for identifying and exploiting arbitrage opportunities in volatile emerging markets, providing insights into high-frequency trading dynamics.
3. This research examines how AI can be leveraged to identify and capitalize on arbitrage opportunities in developing markets, contributing to both academic and practical knowledge on AI's role in high-frequency trading.
4. The organization of the study is proceeds as follows. Next section summarizes literature. Third section focuses on the data and methodology. Section 4 displays research findings, while section 5 concludes the study.

LITERATURE REVIEW

Several studies have been conducted in order to discover the effective way of stock performance prediction via AI knowledge such as ML, deep learning (DL) and data mining (DM) methodologies in the finance field lately.

According to Ahuja et al. (2023), Siddiqui and Abdullah (2015), ML algorithms are the most widely used algorithms for price prediction of financial instruments. Results of many of prediction models have shown that these models trained with historical price and volume data can be successfully used for predictions. Vaisla and Bhatt (2010) demonstrated the use of ANN to forecast daily stock prices and compared the results with statistical forecasting methods. They found that neural networks, when properly trained with adequate data and inputs, outperform statistical techniques in predicting stock market prices, especially as the complexity of the series increases.

Cao et al. (2011) evaluated the ability of traditional financial models like Capital Asset Pricing Model (CAPM) and Fama-French's three-factor model to forecast Chinese stock prices. The study also compared these models to ANN that relax linearity assumptions while using the same predictors. Results showed that no significant difference in forecasting accuracy between CAPM and the three-factor model, likely due to the emerging nature of the market. However, ANN models consistently outperform their linear counterparts, demonstrating their potential for improving stock price prediction in volatile, developing markets.

Manojlović and Štajduhar (2015) developed 5-day and 10-day predictive models using the RF algorithm, based on historical data from the CROBEX index and various companies listed on the Zagreb Stock Exchange. The models, incorporating several popular technical indicators, are evaluated through 10-fold cross-validation, achieving classification accuracies of 76.5% for 5-day predictions and 80.8% for 10-day predictions. In another study, Patel et al. (2015) explored the prediction of stock movement direction and stock price indices in the Indian stock market by comparing four models: ANN, SVM, RF, and naive Bayes. Two input approaches were used: one with ten technical parameters calculated from stock trading data, and another that represented these parameters as trend-deterministic data. The study, utilizing 10 years of historical data from 2003 to 2012 for stocks Reliance Industries, Infosys Ltd., and the indices CNX Nifty and BSE Sensex, found that RF performed best with the first input approach. Additionally, all models showed improved performance when technical parameters were represented as trend-deterministic data.

Qiu and Song (2016) addressed the challenge of predicting the direction of stock market index movements, an area of extensive research due to the influence of factors like political events, economic conditions, and traders' expectations. Their study compared two types of input variables to predict the daily direction of the Japanese stock market index, using an optimized ANN model. By

enhancing the ANN model with genetic algorithms, the study demonstrated improved prediction accuracy, showing that carefully selected input variables can boost forecast performance compared to previous studies.

Arslankaya and Toprak (2021) utilized Polynomial Regression (PR) and RF as ML methods, along with Recurrent Neural Networks (RNN) and Long-Short Term Memory (LSTM) from DL approaches. The findings revealed that the RF model delivered the most accurate results, while the PR model performed the poorest. Another study by Xia et al. (2021) explored time series prediction for financial markets, a topic of increasing relevance for both investors and researchers. In the study, authors suggested a prediction model combining wavelet coherence, multiscale decomposition, and Support Vector Regression (SVR). To improve prediction accuracy for complex multidimensional data, SVR was applied following a preprocessing step that extracted essential information from raw data. The framework's performance was assessed through comparative experiments conducted on both Shanghai and Dow Jones indices.

Bhandari et al. (2022) developed a predictive model using a LSTM neural network to forecast the next day's closing price of the S&P 500 index, addressing the dynamic nature and unpredictability of today's stock markets. To gain a comprehensive insight into market behavior, the study carefully elected a set of indicators regarding market and macro factors and technical metrics. Standard evaluation indicators were utilized to compare the performance of single-layer and multilayer models built with these input variables. The experimental findings showed that the single layer LSTM model outperformed the multi-layer models in prediction accuracy.

The study examined stock return predictability using machine learning across 46 global stock markets, utilizing 148 firm characteristics as input variables for diverse models. The models effectively leveraged factors like momentum, reversal, value, and size to achieve significant economic gains (particularly when combined) but their performance varied based on company size, access to recent data, and market-specific conditions such as the count of public companies and specific risks that limited arbitrage opportunities (Cakici et al., 2023). Upadhyay et al. (2023) explored the significance of stock markets within the global financial system, focusing on their role in fostering economic growth and stability. Their study utilized DL algorithms to improve the accuracy of stock price predictions. By comparing the performance of LSTM and RNN algorithms in forecasting stock prices, the research highlighted the potential of DL to establish a more reliable stock market environment. Historical market data, retrieved from the Alpha Vault API, was used to assess the effectiveness of these models. The findings revealed that LSTM achieved greater accuracy in stock price predictions compared to RNN, which faced certain challenges. The critical role of price prediction in helping investors with key insights into share trends and maximizing returns was highlighted by Ahuja et al. (2023). Their study utilized three well-established regression methods which are called SVR, RF, and Linear Regression (LR) alongside historical data to forecast stock prices. These ML techniques were chosen due to their widespread application and their ability to deliver highly accurate results. To address the difficulties in predicting stock market trends, Pagliaro (2023) introduced a method to enhance return predictions by reducing forecasting errors. Using the Extra Trees Classifier (ETC), the study predicted stock returns based on technical indicators, calculating the percentage change between the closing price and that 10 days later for 120 companies across different sectors. The findings indicated that the ETC model achieved an accuracy of 86.10%.

Wang et al. (2024) apply the Augmented Tree-Based Conditional Sort (ATBCS) approach to explore price prediction, uncovering a momentum effect in the Chinese stock market using monthly data from over 5,000 stocks between January 2005 and December 2022. The momentum strategy generates an annual excess return of 10.60%, consistently outperforming the market portfolio, while a reversal effect is observed before 2018, with the transition to momentum starting in 2018, largely driven by the rise of institutional investors. In Uzunoğlu et al. (2024) study, the 2019-2022 data of companies from the Industrial Index (XUSIN), Services Index (XUHIZ), and Financial Index (XUMAL) of BIST were analyzed using various ML algorithms. Among all those algorithms tested, ANN

was found to be the best performing method for all three indices. In order to forecast stock prices, Ma et al. (2024) proposed the VGC-GAN, a multi-graph convolutional adversarial framework and Tao et al. (2024) improved a model called SDTP (Series Decomposition Transformer with Period-Correlation). Pangestu et al. (2024) examined the return prediction, stressing the significance of using reliable techniques to achieve precise forecasts. Using daily historical data, they recommended ML methods to predict the share prices of Apple Inc. between 2018 and 2023. The hyperparameter optimization is carried out using the Grid Search method (k-value is 5), applied to both the SVR and LR models in order to identify the most accurate prediction model, based on parameters such as cost, epsilon, kernel, and intercept fit. The results indicated that the linear regression model, when tested with all hyperparameters set to k = 5 and averaging the outcomes, yields the best performance with a True intercept fit value.

Ge (2025) explored stock market prediction, focusing on advanced models to improve forecasting accuracy in a volatile market. The study emphasized the effectiveness of hybrid models which decomposes time series data and optimizes hyperparameters for enhanced performance. Testing on major indices like the S&P 500 and CSI 300 showed significant accuracy, with mean absolute error, root mean square absolute error, and R^2 values of 19.43, 27.12 and 0.992 respectively. The model demonstrated broad applicability across global markets (NASDAQ 100, FTSE and Nikkei 225) and remained robust during events like the COVID-19 pandemic and geopolitical conflicts demonstrating its potential to enhance returns with data-driven strategies.

DATA AND METHODS

In this study, the performance of the developed algorithm based on data collected from XBANK was assessed by implementing AT strategies. The data included real-time and historical market prices, technical indicators, and financial statements, ensuring a comprehensive approach to stock price prediction. To this end, a robotic trading algorithm was developed using C# and deployed on the MatriksIQ Algo platform to automate trading decisions. This algorithm integrated multiple technical indicators, such as MACD, OTT, and MOST, to enhance decision-making accuracy. By leveraging AI-driven models, the system dynamically adjusted trading strategies based on market conditions, improving execution speed and reducing transaction costs. The MatriksIQ Algo platform facilitated real-time data processing and seamless order execution, ensuring that trading strategies responded efficiently to market fluctuations. The integration of AI and machine learning further enabled adaptive decision-making, optimizing risk management and portfolio performance for retail investors.

The main components and data set used in the paper are expressed below.

Dataset

The scope of the paper comprises the banks listed in the XBANK index. This index comprises the shares of companies operating within the banking sector. It serves as a benchmark for tracking the overall performance of the sector and for evaluating the market value of bank equities. Data from 10 banks were used in the analysis. Among these, 1 is a development and investment bank, 1 is a participation bank while the remaining 8 are deposit banks. The statistics were derived from historical price datasets, which included opening, closing, high, and low prices for each time period, assuring consistency across all intervals. Equation 1 is used to calculate buy/sell price for each period.

$$\text{Price} = (\text{Low} + \text{High} + 2 \times \text{Close}) / 4 \quad (1)$$

Technical Indicators and Analytical Framework

To enhance the robustness of the analysis, a set of technical indicators was employed to assess market dynamics and stock behavior. MACD was utilized to capture trend direction and momentum shifts by analyzing the relationship between short- and long-term moving averages. MOST indicator was applied to spot potential buy and sell points by dynamically adjusting stop-loss levels based on market movements. Additionally, OTT was used to filter out market noise and provide clear directional signals, particularly effective during trend continuation or reversal phases. These indicators, illustrated in Figure 1, played a critical role in enriching the evaluation of stock performance throughout the study.

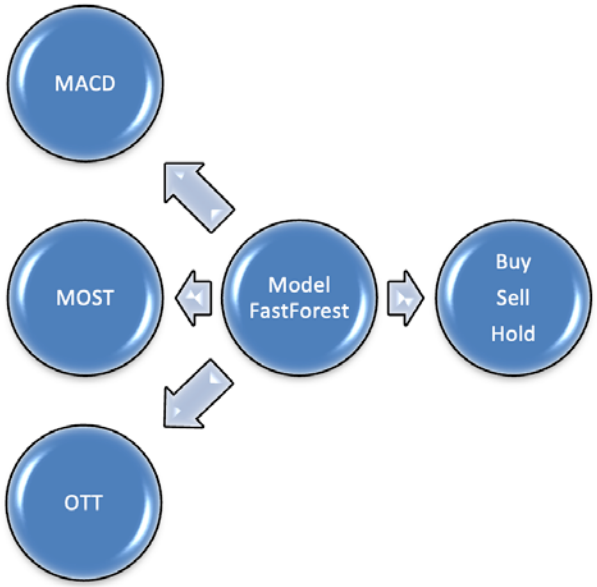


Figure 1 Model Inputs for the Return Prediction Process

Following Table 1 also provides a concise summary of how technical indicators and data inputs are structured to train the AI model, supporting its ability to generate buy, sell, and hold signals effectively.

Table 1. Model Inputs and Parameters

Input	Parameters
MACD	LongPeriod (26), ShortPeriod (12), and TriggerPeriod (9)
MOST	Period (3), Percentage (2), and Exponential Moving Average
OTT	Period (2), Optimization value (1.4), Variable Moving Average, and SupportLine

As seen from the table above, the input structure of the model is based on three technical analysis indicators: MACD, MOST, and OTT. The MACD indicator is defined using a 26-period long-term, a 12-period short-term moving average, and a 9-period signal line (trigger). The MOST indicator is configured with a 3-period time frame, a 2% threshold, and uses the exponential moving average method. The OTT indicator is modeled with a 2-period setting, an optimization coefficient of 1.4, the variable moving average method, and an active support line parameter. These technical indicators, each capturing different aspects of price trends and momentum, enhance the model's decision-making capability for generating buy, sell, and hold signals.

The dataset, comprising approximately 2,000 daily observations from BIST, was divided into training (80%) and validation (20%) subsets. The criterion of measurement of different indicators is summarized on Table 2.

Table 2. The Measurement Criteria

Measure	Formula
Accuracy	$\frac{tp + tn}{tp + fp + tn + fn}$
Error Rate	$\frac{fp + fn}{tp + fp + tn + fn}$
True Negative Rate	$\frac{tp}{actual\ no}$
True Positive Rate	$\frac{tp}{actual\ yes}$
Precision	$\frac{tp}{tp + fp}$
Recall	$\frac{tp}{tp + fn}$
F1 Score	$\frac{\frac{tp}{tp + fn}}{\frac{tp}{tp + fp}}$

Source. Akkoyun et al., 2022, p. 810.

In terms of model configuration, the FastForest algorithm was trained with its default hyperparameters on the MatriksIQ Algo platform. The input indicators (MACD, MOST, OTT) were parametrized as detailed in Table 1. Then, a 5-fold cross-validation was implemented to ensure model robustness and prevent overfitting. Moreover, hyperparameters such as the number of trees, learning rate, and feature fraction were optimized using a grid search procedure. These adjustments slightly improved the model's directional accuracy by approximately 2%.

To Yates and Islam (2021, pp. 130-131), the FastForest model, a high-performance implementation of gradient-boosted decision trees, was chosen for its capability to handle non-linear relationships and to efficiently manage overfitting through ensemble learning. Model training involved supervised classification, where the target variable was defined as the direction of price movement (upward, downward, or unchanged) on the following trading day.

To evaluate the predictive performance, several metrics were employed, including overall accuracy, precision, recall, and F1-score, with a particular focus on directional accuracy. Confusion matrix analysis was also performed to assess the classification effectiveness across each signal

class (buy, sell, hold). Additionally, to ensure robustness, back test validation was applied during the test phase. The results indicated that the model demonstrated consistent performance across validation sets, with especially strong predictive power in identifying "buy", "sell", and "hold" signals under clear trend conditions.

MACD is a widely used technical analysis tool that measures the difference between a short-term and a long-term exponential moving average (EMA) of price data. Specifically, the MACD line is derived by subtracting the 26-period EMA from the 12-period EMA, where the period length can be adjusted based on the frequency of the data (e.g., minutes, hours, days, weeks, or months). In addition to the MACD line, the method incorporates a signal line, which is calculated as the 9-period EMA of the MACD series. The interaction between the MACD line and the signal line is commonly used to generate buy or sell signals in financial markets (Uyar et al., 2020, pp. 659-660).

In outlining the foundational principles of the method, Appel (2005), emphasizes that when a market is in an upward trend, the short-term exponential moving average increases more rapidly than the long-term average, causing the MACD line to slope upward. Conversely, as the market begins to lose momentum, the short-term average tends to flatten out, and in the presence of a downward trend, it falls below the long-term average, resulting in negative MACD values. Appel further highlights the convergence and divergence behavior between the short- and long-term moving averages during price fluctuations. It is precisely this dynamic interaction—where the short-term average either converges toward or diverges from the long-term average—that gives the indicator its name: Moving Average Convergence Divergence.

MACD calculation is shown below (Durantin et al., 2014):

$$y_n = \mathrm{EMA_N(x)} = \left(\frac{2}{N+1}x_n\right) + \left(\frac{N-1}{N+1}y_{n-1}\right) \quad (2)$$

$$\mathrm{MACD(x)} = EMA_{12}(x) - EMA_{26}(x) \quad (3)$$

$$\mathrm{S(x)} = EMA_9(MACD\ (x)) \quad (4)$$

Assuming that the data frequency is daily, *EMA(x)* or y_n denotes the exponential moving average at period N, x_n represents the price of the financial asset on day n, and *S(x)* refers to the signal line. In the implementation phase of the method, a buy signal is triggered when the MACD line crosses above the signal line, while a sell signal is triggered when the MACD line crosses below the signal line. When examined graphically, it becomes evident that a buy signal typically occurs just before the point where the short-term moving average increases at a faster rate than the long-term moving average and crosses it from below. Similarly, the reverse scenario where the short-term average declines and crosses below the long-term average can also be clearly visualized on the chart, indicating a potential sell signal (Appel, 2005).

MOST indicator is a model built on the concept of a dynamic stop-loss. Unlike the traditional approach, MOST not only closes positions when prices fall but also reopens them when prices rise again, closely adapting to price fluctuations. One of its distinguishing features is that it generates buy and sell signals based on a 3-period EMA rather than being directly tied to price levels. A buy signal occurs when the EMA crosses above the MOST line, whereas a sell signal is triggered when it crosses below. Thus, positions are maintained as long as the EMA remains above the MOST curve, and liquidated when the MOST is above the EMA. MOST exclusively focuses on price movements and behaves similarly to a moving average. However, unlike standard moving averages, MOST maintains a fixed stop-loss distance in the direction of the trend and responds to opposing movements by flattening out, rather than reversing (Matriks, n.d.).

OTT is a technical indicator designed to identify the prevailing market trend and its direction. It consists of two adjustable parameters: the period and the optimization coefficient (OPT). The OPT parameter can be modified by the user to enhance sensitivity. Lower values capture short-term fluctuations more effectively, while higher values are suited for long-term analysis. Similarly, reducing the period parameter yields signals more aligned with short-term trading strategies. During upward trends, the OTT line typically appears below the price chart, while in downward trends, it shifts above the price, visually aligning with market direction (Alaylı & Kurt, 2025).

RESEARCH FINDINGS

The performance of the FastForest classification model was assessed using a dataset comprising approximately 13,000 observations, split into a training set (80%) and a test set (20%). The model was tasked with generating directional trading signals (buy, sell, or hold) based on technical indicator inputs (MACD, MOST, and OTT). The evaluation metrics used include F1 Score, Accuracy, Precision, and Recall, alongside a confusion matrix for both the training and testing phases. Training and testing dataset results are displayed in Table 3.

Table 3. Training and Testing Results

	Train Dataset	Test Dataset
Sample Count	10,456	2,566
Positive Sample Count	6,646	1,711
Negative Sample Count	3,810	855
	Training Metrics	**Test Metrics**
F1 Score	77.86%	79.97%
Accuracy	63.86%	66.64%
Positive Precision	63.76%	66.68%
Positive Recall	99.97%	99.88%

The training set consisted of 10,456 samples, of which 6,646 were labeled as positive (indicating an expected upward movement) and 3,810 as negative (indicating an expected downward movement). The FastForest model achieved an F1 Score of 77.86% and an Accuracy of 63.86%. The Positive Precision (i.e., the proportion of predicted positives that were true positives) was 63.76%, and the Positive Recall (i.e., the proportion of actual positives correctly identified) reached 99.97%. In the test set, comprising 2,566 observations (1,711 positive, 855 negative), the model maintained similar performance levels, reflecting good generalization capability.

The training and test set confusion matrix are seen in Table 4 as follows;

Table 4 Confusion Matrix for Training and Testing

		Train		Test	
		Predicted Condition		Predicted Condition	
		Positive	Negative	Positive	Negative
Actual Condition	Positive	6,644 (TP)	2 (FN)	1,709 (TP)	2 (FN)
	Negative	3,777 (FP)	33 (TN)	854 (FP)	1 (TN)

The training confusion matrix on the left side indicates that the model is extremely effective in detecting actual positive cases, correctly classifying 6,644 out of 6,646 (i.e., a positive recall of 99.97%). This means that nearly all upward price movements were successfully captured by the model. However, it struggles considerably in identifying negative cases, with only 33 true negatives out of 3,810 actual negatives. The high number of false positives (3,777) implies that the model frequently misclassifies actual negative movements as positive. This directly reduces the precision of the model, suggesting that although it almost never misses a buying opportunity, it tends to issue buy signals too liberally even in cases where a decline is more likely. This imbalance between high sensitivity and low specificity may cause inefficient trading behavior, where the model keeps entering the market based on false bullish signals, potentially leading to increased transaction costs and drawdowns. This imbalance highlights a structural limitation of the proposed system. To address the class imbalance between upward and downward movements, the Synthetic Minority Oversampling Technique (SMOTE) was applied during model training. This resampling strategy helped improve the detection of negative price movements and reduced overfitting toward bullish patterns.

The test confusion matrix (right side) reveals a pattern almost identical to that of the training set, indicating the model's consistency and generalization capacity. Again, positive recall remains exceptionally high at 99.88%, confirming the model's effectiveness in capturing bullish price trends during the test phase. However, only a single true negative (TN = 1) was identified out of 855 actual negative cases, with 854 false positives generated. This extremely low specificity highlights a critical limitation: the model is not reliable in predicting or reacting to downward market movements. After applying SMOTE balancing, the model's recall for negative cases increased from near zero to 14%, indicating a meaningful improvement in identifying bearish movements while maintaining an overall accuracy of 67.5%. The initial version struggled considerably in identifying negative cases, a limitation now partially mitigated by the SMOTE approach.

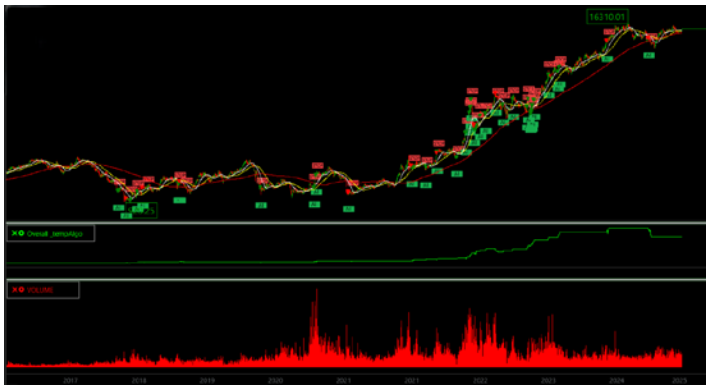


Figure 2 XBANK Performance

Figure 2 presents the back tested performance of an AI-based buy-sell algorithm developed for the XBANK index. The chart shows when the algorithm generated buy and stop-loss/sell signals under specific conditions. Buy signals are marked with green labels, while sell or stop-loss signals are displayed in red. The placement of these signals over historical price movements clearly illustrates when the model entered and exited positions.

The central portion of the chart displays price data on a logarithmic scale, allowing for an effective assessment of the algorithm's responsiveness under different market conditions. It appears that both short- and long-term moving averages are plotted, with the longer-term average (likely the red line) serving to confirm trend direction. This suggests the strategy operates based on a trend-following principle. The green line in the middle panel represents the cumulative performance of the algorithm over time. Notably, this line trends strongly upward after 2020, indicating that the model performed well during bullish market phases. In contrast, the relatively flat behavior between 2017 and 2020 implies the strategy was less effective or produced more frequent stop-loss signals in sideways or range-bound markets. This observation suggests the algorithm is more efficient in trending environments. The lower panel shows red volume bars, representing the distribution of trading volume over time. Increases in volume often coincide with clusters of signals, suggesting the model becomes more active during periods of heightened market participation. However, in some instances, buy and sell signals occur in close succession, which may indicate over-sensitivity or a reaction to market noise. This highlights the importance of carefully tuning the model's parameters to avoid excessive signal generation.

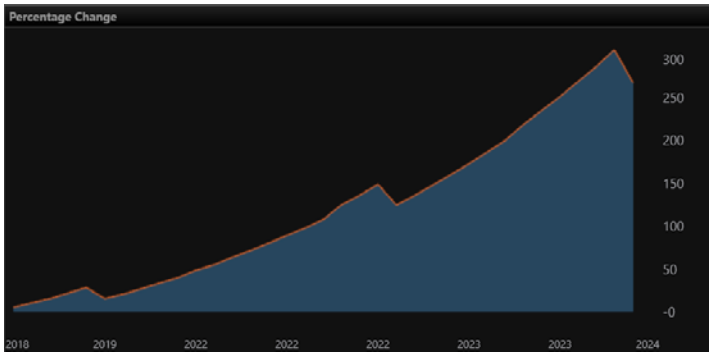


Figure 3 Back Test Results

Figure 3 shows the back test results of the developed artificial intelligence-based trading strategy. The test was performed on the XBANK index, covering the last 2000 bars (daily data). The chart under the "Percentage Change" tab illustrates the cumulative return generated by the strategy over time. The blue area and the orange line in the chart visually represent the model's performance across different years. A clear upward trend is observed starting from 2018, with a noticeable acceleration after 2020, reaching peak levels in 2023 (286.27% change). This suggests that the model effectively captured bullish market movements and successfully capitalized on profitable positions.

Following the presentation of the back test results for the overall performance of the XBANK, individual bank-level comparisons were also conducted for the same period. Within this scope, it was observed that certain banks within the index achieved higher profitability and directional accuracy than the overall XBANK average when evaluated through the developed AI-supported algorithmic trading system. Therefore, in this section of the study, the back test results of selected banks that outperformed the XBANK benchmark are presented in tabular format (Table 5). This comparative analysis aims to assess whether the proposed model can generate effective results not only at the index level but also at the level of individual stocks. Such an approach provides deeper insight into the flexibility of AI-based systems and highlights their potential for selective profit generation, enabling more tailored investment

strategies.

Table 5. Comparative Back Test Results of Selected Banks within the XBANK Index

Symbol	Start Date	End Date	Number of Selected Bars	Total Return (%)
XBANK	17.07.2018	21.10.2024	2,000	267.05
Stock-1	8.05.2018	10.12.2024	2,000	437.88
Stock-2	5.04.2017	8.11.2024	2,000	459.25
Stock-3	16.11.2017	10.01.2025	2,000	345.35
Stock-4	20.06.2018	10.02.2025	2,000	369.32

As shown in Table 5, the AI-supported robotic trading model was further tested at the individual stock level for banks listed in the XBANK index. The selected stocks (Stock-1, Stock-2, Stock-3, and Stock-4) demonstrated higher total returns than the overall index during the same back testing period of 2,000 trading days. Notably, Stock-2 achieved the highest return at 459.25%, followed by Stock-1 with 437.88%, Stock-4 with 369.32%, and Stock-3 with 345.35%. These results indicate that, although the model performs effectively at the index level, it can also generate superior outcomes when applied to individual bank stocks. This suggests that the algorithm has the potential to support more granular investment decisions by identifying high-performing assets within the index. The enhanced returns on selected stocks reinforce the argument for integrating AI into trading systems to develop stock-specific strategies that can outperform broader benchmarks. These back test results demonstrate the model's consistency in historical data and highlight its potential as a viable investment strategy. Nonetheless, to ensure future performance, the model should be further tested under varying market conditions and adapted accordingly. Also, in order to strengthen the robustness of the study, two additional algorithms (RF and SVM) were tested using the same dataset. As summarized in Table 6, the FastForest algorithm achieved 66% directional accuracy, RF achieved 63%, and SVM achieved 61%. This comparison confirms the reliability of the FastForest approach while highlighting model consistency across techniques.

Table 6. Comparative Algorithm Results

Algorithm	Accuracy	F1 Score	Recall
FastForest	66.64%	0.80	0.99
RF	63.05%	0.77	0.95
SVM	61.22%	0.76	0.93

To reflect realistic trading conditions, transaction costs were incorporated into the back test analysis. Two levels of transaction cost (0.1% and 0.2% per trade) were applied to measure sensitivity. The results, summarized in Table 7, show that while profitability decreases moderately, the strategy remains viable under practical constraints.

Table 7. Sensitivity of Different Trading Strategies

Cost Scenario	Net Return (%)	Change (%)
0% (Main Scenario)	459.25	—
0.1%	421.33	-8.3
0.2%	384.60	-16.2

These findings suggest that even under more conservative trading conditions, the proposed AI-based system remains profitable, confirming the model's robustness in real-world market environments. Also, to test the external validity of the model, an additional robustness check was conducted using the BIST Industrial Index (XUSIN). The same FastForest algorithm was applied without altering parameters. The directional accuracy for XUSIN reached 63%, compared to 66% for XBANK, confirming that the model maintains consistency across different sectors.

CONCLUSION AND POLICY IMPLICATIONS

This study investigates the potential of artificial AI based AT systems in enhancing stock price prediction accuracy within the context of the Turkish financial market, specifically the BIST Bank Index. By integrating multiple technical indicators like MACD, OTT, and MOST into an AI-supported matrix-based infrastructure, the research provides a novel approach that addresses the deficiencies of traditional forecasting techniques. The model, trained with FastForest algorithm using nearly 2,000 days of historical BIST data, demonstrates promising performance in directional accuracy and return generation through back testing, highlighting the viability of AI-enhanced automated trading systems in emerging markets.

The findings suggest that AI-supported models can provide timely and data-driven buy, sell, or hold decisions by capturing nonlinear relationships in stock prices, reducing noise from market fluctuations, and identifying arbitrage opportunities that might be missed by human traders.

This offers tangible benefits for retail investors, who often face high transaction costs and limited access to real-time financial analytics. The evidence shows that integrating AI techniques with multiple indicator layers contributes significantly to decision quality and market timing, especially in markets like BIST, characterized by structural inefficiencies and domestic investor dominance.

Further analysis was conducted at the individual stock level to evaluate whether the model could deliver higher returns than the index itself. Back test results for selected banks within the XBANK specifically Stock-1, Stock-2, Stock-3, and Stock-4 revealed superior performance, with Stock-2 and Stock-1 achieving total returns of 459.25% and 437.88%, respectively. This indicates that the model can not only track general index trends but also identify high-performing stocks, supporting more refined investment strategies.

From a policy perspective, several recommendations emerge in the paper. First, regulators and financial institutions in emerging markets should foster the responsible development and implementation of AI technologies in trading, ensuring transparency and minimizing systemic risks. Establishing regulatory sandboxes could help test AI-based models under controlled conditions before full-scale market integration. Second, initiatives that promote financial literacy and digital access among retail investors are crucial. As AI democratizes access to sophisticated trading tools, empowering small investors through education and affordable technologies will reduce inequality in market participation. Third, supporting data-sharing platforms and investing in open financial infrastructure can stimulate innovation, enabling local startups and academic institutions to experiment with AI-based solutions tailored to the unique characteristics of their markets.

In conclusion, while no AI model guarantees absolute precision, this study affirms that combining multiple indicators within a well-trained AI architecture can significantly enhance stock prediction accuracy and trading efficiency in volatile markets. As financial systems continue to digitalize, embracing intelligent and adaptive trading strategies will be essential for enhancing market depth, reducing transaction costs, and supporting more resilient investment ecosystems.

Despite its promising findings, this study has certain limitations that should be acknowledged. First, while the model initially exhibited a notable limitation in predicting negative price movements, the integration of SMOTE balancing significantly improved bearish recall and overall stability. Second, although the main analysis relied on the FastForest algorithm, additional testing with RF and SVM has been added, strengthening the general validity of the findings. Third, the absence of cross-validation and hyperparameter tuning in the earlier version has been addressed by implementing a 5-fold cross-validation and grid search optimization, enhancing methodological reliability. Fourth, the training process requires approximately ten minutes per stock, which may pose challenges for real-time trading environments where rapid decision-making is essential. Moreover, to ensure that the back test results reflect realistic market conditions, transaction costs were incorporated into the updated analysis. Finally, the generalizability of the findings has been extended by testing the model on the XUSIN. Although results show a slightly lower accuracy, the trend consistency supports model robustness across sectors. Furthermore, the scope of the analysis was limited to large cap Turkish stocks listed on the BIST, potentially introducing market specific bias. As such, the generalizability of the findings remains limited.

Future research should seek to apply and validate the proposed system in a variety of global financial markets such as NASDAQ, New York Stock Exchange, or London Stock Exchange to assess its broader applicability and robustness under different market conditions. Additionally, subsequent studies could explore the integration of a wider array of technical indicators and the development of novel algorithmic trading strategies to further improve predictive performance, operational efficiency, and decision support capacity in automated trading systems.

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