Trakya Üniversitesi Sosyal Bilimler Dergisi
2025 Cilt 27 Özel Sayı (275-302)
DOI: 10.26468/trakyasobed.1514346
Araştırma Makalesi/Research Article

WHEN MACHINES LEARN TECHNICAL ANALYSIS: AN APPLICATION ON TECHNICAL ANALYSIS WITH MACHINE LEARNING IN BORSA ISTANBUL[1]

MAKİNELER TEKNİK ANALİZ ÖĞRENDİĞİNDE: BORSA İSTANBUL'DA MAKİNE ÖĞRENMESİ İLE TEKNİK ANALİZ ÜZERİNE BİR UYGULAMA

Yunus Emre AKDOĞAN[*]

Geliş Tarihi:14.07.2024 (Received) *Kabul Tarihi:13.03.2025 (Accepted)*

ABSTRACT: There are two approaches to analyzing the value of a stock in financial markets: fundamental analysis and technical analysis. While fundamental analysis focuses on finding the intrinsic value of a stock based on a company's financial condition and current market conditions, technical analysis focuses on identifying trading signals in patterns by examining historical price behavior and statistics. Although technical analysis, which is based on the assumption that past price movements can be an indicator for future price movements, has a predefined set of rules, the interpretation of the results is closely related to the experience of the analyst. Therefore, the interpretive part of technical analysis has a subjective dimension. This subjective dimension and predefined set of rules indicate that machine learning methods with experience-based learning logic can be an important tool in identifying trading signals or predicting price movements. The aim of this study is to investigate the potential use of machine learning algorithms that use technical analysis indicators of stocks traded in Borsa Istanbul as input to predict the direction of the price up or down. In the study, technical analysis indicators are analyzed with models based on machine learning methods and the results are compared. The findings show that the addition of machine learning methods to technical analysis strategies increases the predictive power of the direction of the price up or down.

Key Words: Technical Analysis, Machine Learning, Artificial Intelligence, Stock Market Forecasting

ÖZ: Finansal piyasalarda bir hisse senedinin değerini analiz etmek için biri temel analiz diğeri teknik analiz olmak üzere iki yaklaşım vardır. Temel analiz bir şirketin mali durumuna ve mevcut piyasa koşullarına bağlı olarak hisse senedinin içsel değerini bulmaya yönelirken teknik analiz tarihsel fiyat davranışlarını ve istatistiklerini inceleyerek örüntülerdeki işlem sinyallerini belirlemeye odaklanmaktadır. Geçmişteki fiyat hareketlerinin gelecekteki fiyat hareketleri için bir gösterge olabileceği varsayımına dayalı olan teknik analizde her ne kadar önceden tanımlanmış kurallar seti olsa da sonuçların yorumlanması analistin deneyimi ile yakından ilişkilidir. Dolayısıyla teknik analizin yoruma açık kısmı öznel bir boyuta sahiptir. Bu öznel boyut ve önceden tanımlanmış

[1] Revised and edited version of the paper presented at IERFM2024 Congress.
[*]Dr. Öğr. Üyesi, Yozgat Bozok Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, emre.akdogan@bozok.edu.tr, ORCID: 0000-0002-1761-2869.

kurallar seti, deneyime dayalı öğrenme mantığına sahip makine öğrenmesi yöntemlerinin, işlem sinyallerinin belirlenmesi ya da fiyat hareketlerinin tahmin edilmesinde önemli bir araç olabileceğine işaret etmektedir. Bu çalışmanın amacı, Borsa İstanbul'da işlem gören hisse senetlerinin teknik analiz göstergelerini girdi olarak kullanan makine öğrenmesi algoritmalarının fiyatın aşağı veya yukarı yönünü tahmin etmek için potansiyel kullanımını araştırmaktır. Çalışmada, teknik analiz göstergeleri makine öğrenmesi yöntemlerine dayalı modeller ile analiz edilmiş ve sonuçlar karşılaştırılmıştır. Elde edilen bulgular, teknik analiz stratejilerine makine öğrenmesi yöntemlerinin eklenmesinin fiyatın aşağı veya yukarı yönünü tahmin etme gücünü artırdığını göstermektedir.

Anahtar Kelimeler: Teknik Analiz, Makine Öğrenmesi, Yapay Zekâ, Borsa Tahmini

1. INTRODUCTION

Determining the value of stocks traded on the stock exchange (Treynor, 1962; Sharpe, 1964; Lintner, 1965; Mossin, 1966; Fama, 1970) and accurately predicting future price movements is one of the fundamental issues of finance theory. However, the complexity and uncertainty inherent in financial markets have given rise to theories and hypotheses with different perspectives and approaches.

The most fundamental of these theories of modern finance is the efficient markets hypothesis. The efficient markets hypothesis argues that asset prices reflect all available information and therefore no one can gain any advantage in the market (Fama, 1965). According to this hypothesis, markets can be efficient in three different forms in terms of information reaching investors. In a weakly efficient market, it is not possible to predict price movements and obtain abnormal returns by making technical analyses with past price data. In the semi-strong form of efficiency, since prices reflect publicly available information in addition to historical price data, it is not possible to obtain abnormal returns by conducting fundamental analysis. In the strong form of market efficiency, it is not possible for those who have access to inside information, such as managers and employees, to achieve abnormal returns by using this information (Fama, 1970).

In this framework, Fama argues that even in a weakly efficient market, the future behaviour of stock prices is independent of the past, that is, it follows a random walk. In this context, the random walk hypothesis states that consecutive price changes are random and therefore it is not possible to predict stock prices (Cootner, 1964; Fama, 1965a; Fama, 1965b). In other words, the random walk hypothesis claims that there are two main approaches to forecasting prices, namely technical analysis and fundamental analysis, but due to the random nature of price formation in the market, neither technical analysis nor fundamental analysis can be used to predict the future price movements of stocks. Therefore, it is extremely difficult to predict stock price movements in the short term. Therefore, they argue that it is a waste of time for investors to use fundamental and technical analysis to predict stock prices, and that it is better to buy and hold an index fund instead (Malkiel, 1973).

Against this view, behavioural finance (Thaler, 2015; Shiller, 2015; Tversky and Kahneman, 1974; Hirshleifer, 2015; Barberis and Thaler, 2003; De Bondt and Thaler, 1995; Shefrin, 2002); fundamental analysis, which attempts to calculate the intrinsic value and potential future value of the firm based on factors such as profitability, revenues, assets, liabilities, industry trends and macroeconomic conditions (Hou, 2011; Ou and Penman, 1989; Abarbanell and Bushee, 1997; Kheradyar et al. 2011; Zhang et al. 2011; Li et al. 2014a; Li et al. 2014b; Rather et al. 2015; Ballings et al. 2015; Sun et al. 2016); technical analysis, which argues that various charts and technical indicators can be used to predict future price movements based on past price and volume data (Bessembinder & Chan, 1995; Sureshkumar & Elango, 2011; Wei, 2011; De Oliveira et al. 2013; Bisoi & Dash, 2014).

In this context, technical analysis is the study of market and price movements using historical price and volume information to predict future price trends. Technical analysis has three basic rationales and assumptions. The first of these is the assumption that the market discounts everything. According to this assumption, everything related to economic, political, psychological or fundamental values that may affect the price is reflected in the prices. Therefore, all that is necessary is to analyse the market price. In other words, since what causes bull and bear markets is the reflection in price movements of changes in supply and demand, which form the basis of all economic forecasts, analysing charts is sufficient to explain the rise or fall of the market. The second assumption of fundamental analysis is that prices move in trends. According to this assumption, trend following is based on the continuation of an existing trend in the same direction until it shows signs of reversal. In this context, the main purpose of looking at the price movements of a market on a trend basis or trend following is to trade by catching trend developments at an early stage. The third assumption of fundamental analysis is that price movements and certain patterns repeat themselves. In other words, this assumption, which is based on the idea that the future is a repetition of the past, argues that defined and categorised chart patterns reflect certain patterns on price characteristics (Murphy, 1999; Kahn, 2009; Rockefeller, 2019).

Despite all these different perspectives and difficulties, developing the ability to predict stock prices is very important for investors to effectively manage risks and develop profitable investment strategies. In this context, although there is a predefined set of rules in technical analysis, the interpretation of the results is closely related to the experience of the analyst. In other words, the ability to interpret a certain price chart pattern or indicator signal as a buying or selling opportunity in technical analysis and to adjust the investment strategy accordingly gives technical analysis a subjective dimension that is open to interpretation. This subjective dimension and predefined set of rules indicate that machine learning methods with experience-based learning logic can be an important tool in identifying trading signals or trends or predicting price movements. Indeed, developments in the field of artificial intelligence and machine learning also point to promising findings to improve the accuracy of stock price prediction (Aït-Sahalia & Xiu, 2018; Bordino et al., 2012). In this context, artificial intelligence is defined as the ability of computers or computer-controlled robots to perform cognitive tasks that intelligent beings can perform, such as sense discovery, reasoning, generalisation, learning from experience and problem solving. Machine learning refers to the methods of training a computer to learn from inputs without explicit programming (Copeland, 2024). Therefore, computers' access to artificial intelligence is basically based on machine learning.

The aim of this study is to investigate the potential use of machine learning algorithms that use technical analysis indicators based on price and volume data of stocks traded on the BIST 50 index in Borsa Istanbul as input to predict trading signals and price movements. In the study, technical analysis indicators are analysed with models based on machine learning methods and the results are compared. The findings show that the addition of machine learning methods to technical analysis strategies increases the predictive power of trading signals and price movements.

In the literature, artificial intelligence is considered at three levels: narrow, general and super. While super artificial intelligence refers to the type of artificial intelligence that has superhuman abilities, general artificial intelligence refers to artificial intelligence designed to fulfil any task that humans can perform. Narrow artificial intelligence refers to artificial intelligence designed to perform a specific task or a limited set of tasks (Russell & Norvig, 2021; Saghiri et al., 2022). Within the scope of narrow artificial intelligence, the findings obtained from this study make an important contribution to the development of financial artificial intelligence applications and the training of bots performing algorithmic financial transactions within the scope of technical analysis learning machines.

2. LITERATURE REVIEW

Lee et al. (2007) created a reinforcement learning-based algorithm intended to offer daily trading recommendations for investors. This system utilizes a multi-agent structure to simulate investor behavior in stock markets. Their approach employed a Q-learning algorithm with four collaborative agents, each possessing distinct functionalities. The initial two agents decide on buying and selling stocks based on trend predictions, while the remaining two agents focus on determining optimal buy and sell prices for executing intra-day orders. Moreover, the order agents were designed to incorporate intra-day price movements using technical analysis methods like short-term moving averages and candlestick charts. Using data from the Korean stock market, the study demonstrated that their proposed trading strategy outperformed alternative models in terms of both risk management and profitability.

Khan et al. (2008) conducted a study where they compared different technical indicators using both a backpropagation neural network and a genetic algorithm-based backpropagation neural network. Their objective was to identify a method that could provide more precise predictions of stock prices. They analyzed price and volume data of a stock traded on the National Stock Exchange of India over a period from January 1, 2004, to December 29, 2006. Their findings indicated that the genetic algorithm-based backpropagation neural network outperformed other techniques in accurately predicting stock prices.

Teixeira and De Oliveira (2010) undertook a study to forecast stock market price trends by integrating technical analysis tools with the k-NN algorithm. Their research aimed to assess the feasibility of an intelligent forecasting system reliant solely on historical daily stock closing prices and volumes. They introduced a method that incorporates stop loss, profit, and RSI filters to enhance prediction accuracy. The study focused on companies listed on the São Paulo Stock Exchange and found that their proposed approach yielded substantial profitability. Consequently, employing this method for predicting short-term stock trends surpassed the profitability achieved through technical analysis alone.

Rodríguez-González et al. (2011) sought to develop a trading system grounded in technical analysis, specifically using feedforward neural networks to improve the accuracy of calculating the Relative Strength Index (RSI), developed by Wilder(1978). The RSI is a momentum indicator assessing the pace and scale of recent price changes in a security. Their study demonstrated that their model could effectively forecast both individual stocks listed on the IBEX 35 index and overall market movements.

Patel et al. (2015) sought to forecast the direction of stock prices and stock indices in the Indian market using four models: Support Vector Machine, Artificial Neural Network, Naive Bayes, and Random Forest. They employed two methods for input data: the first involved calculating ten technical parameters from stock trading data, while the second involved representing these parameters as trend indicators. The study examined two stocks, Reliance Industries and Infosys Ltd., as well as two indices, CNX Nifty and S&P BSE Sensex, using historical data from 2003 to 2012. The findings revealed that the Random Forest model performed best in the first method with continuous technical parameters. Moreover, in the second method, where technical parameters were trend-based, all models showed improved performance.

Sezer et al. (2017) created a stock trading model leveraging genetic algorithms and technical analysis parameters. They employed the Apache Spark big data platform along with the Spark MLlib library to evaluate data from Dow 30 stocks spanning from 1996 to 2016. The study used RSI and SMA values as technical indicators. Findings indicated that optimizing these parameters using genetic algorithms enhanced stock trading performance. Furthermore, the proposed model outperformed conventional technical analysis models.

Agrawal et al. (2019) investigated three prominent indices from the National Stock Exchange of India—Bank, Auto, and Metal—to assess whether utilizing stock technical indicators and modern deep learning algorithms could enhance profit margins and aid in both long-term and short-term trading decisions. Their focus was on predicting future prices and trends of stock indices to precisely identify entry and exit points for investments. They employed Long Short-Term Memory (LSTM) networks, using TensorFlow and Keras libraries, to integrate highly correlated stock technical indicators into their prediction model. The study demonstrated that their model could accurately classify monthly trends as profit, loss, or neutral. Additionally, they achieved up to 68.45% accuracy, with an average accuracy of 61.51% in their daily predictions.

Ayala et al. (2021) sought to create a trading strategy by integrating technical analysis indicators with machine learning techniques, focusing on the DAX, IBEX, and Dow Jones Industrial (DJI) indices. They utilized technical indicators like the Triple Exponential Moving Average and Moving Average Convergence/Divergence to devise the trading strategy. Several machine learning methods—including Linear Model, Random Forest, Artificial Neural Network, and Support Vector Regression—were tested to determine the best performer. The findings revealed that combining machine learning techniques with technical analysis strategies produced more reliable trading signals.

Pxardeshi and Kale (2021) analyzed daily data from 2015 to 2019 for the 25 highest-trading-volume companies on the National Stock Exchange of India. They compared technical analysis indicators such as RSI, exponential moving averages, Heiken Ashi candlesticks, price-volume analysis, and MACD with machine learning algorithms including Naïve Bayes classifier, neural networks, and k-NN. Their findings indicated that as the number of days increased, the accuracy of the indicators and the likelihood of making a profit also increased. Furthermore, they concluded that there was no significant difference in performance between traditional technical analysis methods and machine learning models such as decision trees, k-NN, random forests, and MLP.

Lee et al. (2021) explored the feasibility and effectiveness of utilizing deep networks and technical analysis indicators to forecast short-term stock price movements. They concentrated on the TWSE 0050, a highly traded ETF on the

Taiwan Stock Exchange, examining data from January 2017 to Q3 2019. They employed the LSTM method to predict stock price trends, incorporating popular technical indicators such as opening price, closing price, daily high and low prices, Williams %R, RSI, KD, BIAS, and MACD. Their results demonstrated that combining these technical indicators with the LSTM model achieved 83.6% accuracy in classifying trends as rising, falling, or flat.

Peng et al. (2021) investigated the use of deep neural network models to forecast stock price direction, utilizing 124 technical analysis indicators as explanatory variables. They analyzed daily data from seven global market indices spanning from 2008 to 2019, experimenting with neural networks featuring various hidden layer configurations. The study revealed that feature selection algorithms did not consistently select the same variables, highlighting the variability in the significance of technical indicators across different models and market conditions.

Kamara et al. (2022) created a hybrid algorithm for stock price prediction that combines independent deep learning models: CNN for short-term signals, LSTM for long-term signals, and an Attention Mechanism for very long-term features. Their study incorporated technical indicators such as Moving Average, MACD curve, RSI, among others. When tested on two NYSE stocks, their approach yielded the lowest error values (MAE, RMSE, MAPE) compared to other datasets.

Albahli et al. (2023) endeavored to predict stock prices by leveraging a decade of stock data and technical indicators. Their model generated buy, sell, or hold signals using a 1D DenseNet and an autoencoder. Technical indicators and stock data were processed through DenseNet-41, and the resulting feature vector was inputted into a SoftMax layer to forecast closing prices across short, medium, and long-term horizons. Their method achieved a minimum MAPE value of 0.41, demonstrating superior performance compared to alternative approaches.

Goutte et al. (2023) investigated the utilization of technical analysis indicators as inputs for machine learning models, focusing on deep learning algorithms to generate trading signals within the cryptocurrency market. They applied several machine learning techniques to five years of hourly Bitcoin data spanning from 2017 to 2022. The findings highlighted that recurrent neural networks, among other methods, generally exhibited superior performance in time series forecasting compared to alternative approaches.

Ayyildiz and Iskenderoglu (2024) sought to forecast the directional movements of stock market indices in developed countries including the USA, Japan, UK, France, Germany, Italy, and Canada, using machine learning algorithms. Their analysis identified artificial neural networks as the optimal algorithm for certain indices, while logistic regression proved to be the best predictor for others. They also concluded that they could predict the movement direction of all indices with an accuracy exceeding 70%.

Khaniki and Manthouri (2024) centered their study on Bitcoin, Ethereum, and Litecoin, employing a Performer neural network and BiLSTM (Bidirectional Long Short-Term Memory). Their approach aimed to capture the temporal dynamics of cryptocurrency time series and extract meaningful features using integrated technical indicators. These indicators facilitated the identification of complex patterns, momentum, volatility, and trends across hourly and daily time frames. Their findings suggested that their proposed method exhibited promising potential to surpass existing models in cryptocurrency forecasting.

3. RESEARCH

3.1. Aim of the Study

This study aims to investigate the potential use of machine learning algorithms that use technical analysis indicators of stocks traded in Borsa Istanbul as input to predict the direction of the price up or down. In the study, various technical analysis indicators are calculated with the TA-Lib module developed for the Python programming language and analyzed with machine learning methods and the prediction success of these methods are compared. Thus, it is investigated whether technical analysis can be taught to machines and whether a product can be produced within the scope of narrow financial artificial intelligence.

3.2. Universe and Sample of the Study

The study covers the 50 firms with the highest market capitalization and trading volume traded in Borsa Istanbul. BIST 50 companies include stocks operating in different sectors and also include BIST 30 stocks.

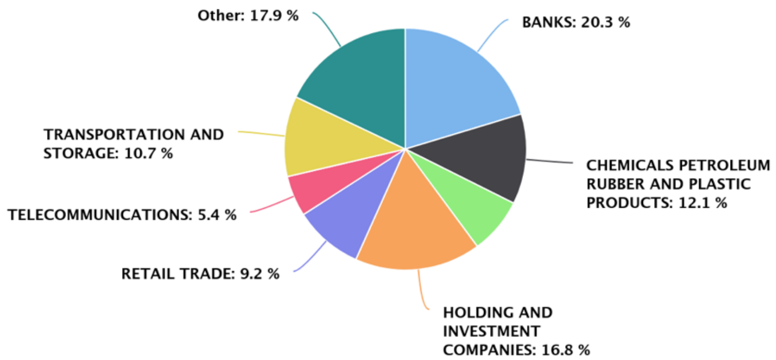

Figure 1: Sectoral Distribution
Source: https://borsaistanbul.com/tr/

As can be seen in Figure 1, 20.3% of the companies in the BIST 50 index are banks, 16.8% are holdings and investment companies, 12.1% are chemicals, pharmaceuticals, petroleum, rubber and plastic products, 10.7% are transport and storage, 9.2% are retail trade, 7.5% are metal goods machinery electrical appliances and transport vehicles, 5.4% are telecommunications and 17.9% are other sector companies. Within the scope of the study, the BIST 50 index, which includes companies in different sectors, was preferred in order to ensure comparability of technical analysis prediction performance with machine learning methods for companies operating in different sectors.

Table 1: BIST 50 Firms in April-June 2024

AKBNK	DOAS	GESAN	MGROS	TAVHL
ALARK	DOHOL	GUBRF	MIATK	TCELL
ALFAS	EGEEN	HALKB	ODAS	THYAO
ARCLK	EKGYO	HEKTS	OYAKC	TOASO
ASELS	ENJSA	ISCTR	PETKM	TTKOM
ASTOR	ENKAI	KCHOL	PGSUS	TUPRS
BIMAS	EREGL	KONTR	SAHOL	ULKER
BRSAN	EUPWR	KOZAA	SASA	VESTL
CIMSA	FROTO	KOZAL	SISE	YKBNK
CWENE	GARAN	KRDMD	SMRTG	ZOREN

Source: Borsa İstanbul (2024)

Within the scope of this study, the companies in BIST 50 in the April-June period of 2024 are given in Table 1.

3.3. Technical Analysis Indicators

Technical analysis indicators are used to determine the future trends of a security based on price and volume data so that investors can make buying and selling decisions. In other words, technical analysis provides tools to determine trends, momentum, volatility, and volume in the market by examining price and volume data (Hale, 2023). In this study, technical indicators are categorized into five groups as overlap, momentum, volume, cycle, and volatility indicators, and a total of 58 variables were calculated and presented in Table 2.

Overlay indicators are technical indicators, also known as lagging indicators, which are drawn over the prices on a chart. This allows traders to identify important support and resistance levels, trend reversals, and potential entry or exit points for their trades. Momentum indicators are technical analysis tools that measure the rate of change in the price of a security over a given time period. These tools, also known as oscillators, are often used in conjunction with other indicators as they focus on the time period in which the price change occurs rather than determining the direction of the movement. Volume is the total amount of a security traded, usually on a trading day. Volume indicators are technical analysis tools that use trading volume data to assess the strength or weakness of a market trend. Volume indicators provide insight into the buying and selling pressure in the market during a given period. Volatility indicators are technical analysis tools that measure the degree of change in the price of a security over time. These indicators help investors determine the level of risk involved in a particular transaction by identifying periods of high or low volatility (Hale, 2023). Cycle indicators are indicators that can be used to analyze regularly repeating market cycles, allowing them to predict price reversals in important cyclical ranges (Chart Formations, 2024).

Table 2: Technical Indicators

T	Short Name	Indicator Name	T	Short Name	Indicator Name
O	BBANDS	Bollinger Bands	M	ADX	Average Directional Movement Index
O	DEMA	Double Exponential Moving Average	M	ADXR	Average Directional Movement Index Rating
O	EMA	Exponential Moving Average	M	APO	Absolute Price Oscillator
O	HT_TRENDLINE	Hilbert Transform - Instantaneous Trendline	M	AROON	Aroon
O	KAMA	Kaufman Adaptive Moving Average	M	AROONOSC	Aroon Oscillator
O	MA	Moving average	M	BOP	Balance Of Power
O	MAMA	MESA Adaptive Moving Average	M	CCI	Commodity Channel Index
O	MAVP	Moving average with variable period	M	CMO	Chande Momentum Oscillator
O	MIDPOINT	MidPoint over period	M	DX	Directional Movement Index
O	MIDPRICE	Midpoint Price over period	M	MACD	Moving Average Convergence/Divergence
O	SAR	Parabolic SAR	M	MACDEXT	MACD with controllable MA type
O	SAREXT	Parabolic SAR - Extended	M	MACDFIX	Moving Average Convergence/Divergence Fix 12/26
O	SMA	Simple Moving Average	M	MFI	Money Flow Index
O	T3	Triple Exponential Moving Average (T3)	M	MINUS_DI	Minus Directional Indicator
O	TEMA	Triple Exponential Moving Average	M	MINUS_DM	Minus Directional Movement
O	TRIMA	Triangular Moving Average	M	MOM	Momentum
O	WMA	Weighted Moving Average	M	PLUS_DI	Plus Directional Indicator
VM	AD	Chaikin A/D Line	M	PLUS_DM	Plus Directional Movement
VM	ADOSC	Chaikin A/D Oscillator	M	PPO	Percentage Price Oscillator
VM	OBV	On Balance Volume	M	ROC	Rate of change : ((price/prevPrice)-1)*100
C	HT_DCPERIOD	Hilbert Transform - Dominant Cycle Period	M	ROCP	Rate of change Percentage: (price-prevPrice)/prevPrice
C	HT_DCPHASE	Hilbert Transform - Dominant Cycle Phase	M	ROCR	Rate of change ratio: (price/prevPrice)
C	HT_PHASOR	Hilbert Transform - Phasor Components	M	ROCR100	Rate of change ratio 100 scale: (price/prevPrice)*100
C	HT_SINE	Hilbert Transform - SineWave	M	RSI	Relative Strength Index
C	HT_TRENDMODE	Hilbert Transform - Trend vs Cycle Mode	M	STOCH	Stochastic
VT	ATR	Average True Range	M	STOCHF	Stochastic Fast
VT	NATR	Normalized Average True Range	M	STOCHRSI	Stochastic Relative Strength Index
VT	TRANGE	True Range	M	TRIX	1-day Rate-Of-Change (ROC) of a Triple Smooth EMA
			M	ULTOSC	Ultimate Oscillator
			M	WILLR	Williams' %R
T: Type, O: Overlap, C: Cycle; VM: Volume, VT: Volatiliy, M: Momentum					

2025 Cilt 27 Özel Sayı (275-302)

3.4. Research Methods

In this study, six different machine learning methods with different computational techniques such as Artificial Neural Networks (ANN), K-Nearest Neighbour (KNN), Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF) and Gradient Boosting (GB) were used and their prediction performances were compared.

3.4.1. Artificial Neural Networks (ANN)

Artificial neural networks, inspired by the neural networks in the human brain, have an architecture that models the transmission of information through neurons and connections between neurons. Artificial neural networks, also referred to as multilayer perceptron (MLP), are basically a feed-forward neural network consisting of three layers: input layer, output layer and hidden layer, as shown in Figure 2. In MLP, data are forwarded from the input layer to the output layer using an activation function that takes into account the non-linearity of the data, and the final prediction is calculated in the output layer. The weights of the connections between neurons are updated by back propagation of prediction errors. The aim of back propagation of errors and updating the connection weights is to minimize the loss function. This is essentially what is referred to as learning in artificial neural networks (Haykin, 1998).

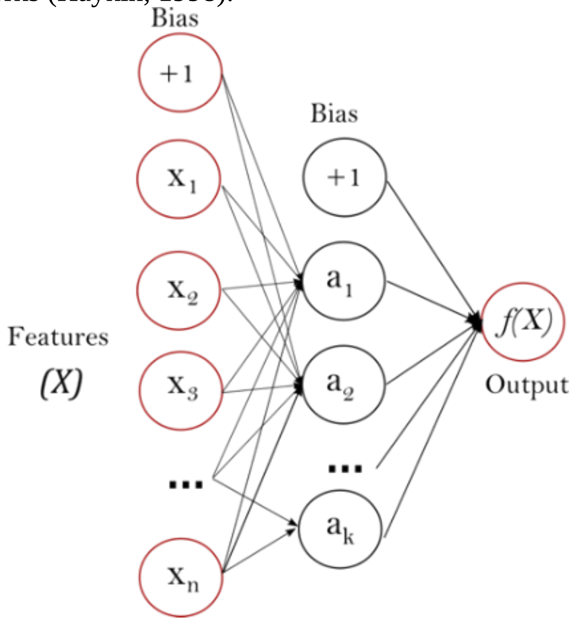

Figure 2: One hidden layer MLP
Source: https://scikit-learn.org/stable/modules/neural_networks_supervised.html

Artificial neural networks can be used to solve both regression and classification problems.

3.4.2. Naive Bayes (NB):

Naive Bayes is a machine learning classification method based on Bayes' Theorem with the assumption that all attributes are independent of each other, i.e. they do not affect each other. The fact that this situation, which is almost impossible to be encountered in real life, is ignored by the Naive Bayes classifier has led to the model being called Naive. The Naive Bayes method is also based on the assumption that all attributes contribute equally to the result and selects the one with the highest probability by calculating the probability of each class. In this context, Equation 1 expresses Bayes' theorem as P(y/x), which denotes the probability of event y occurring given that event x has occurred (Jordan & Mitchell, 2015).

$$P(y|x) = \frac{P(y|x)P(y)}{P(x)} \quad 1$$

3.4.3. K-Nearest Neighbors (KNN):

The K-Nearest Neighbors algorithm calculates the distance of each observation in the dataset to other observations and uses these distances as the basis for solving the classification problem. In this method, the point with the shortest distance to the data point is called the nearest neighbor. In the KNN technique, in order to define the class of any data point in the dataset, the number of nearest neighbors to be considered is calculated according to the value of k (Bhatia, 2010). In other words, the k value in the nearest neighbors algorithm refers to the k observations that are closest to a data point compared to other observations and classification is performed by majority voting of the nearest neighbors (Laaksonen & Oja, 1996; Zhang & Wang, 2016). Choosing a small value of k causes similar points to be classified as belonging to different classes, while choosing a high value causes dissimilar points to be grouped together (Beyer et al., 1999). In the KNN algorithm, various distance calculation criteria such as Euclidean distance, Manhatta distance, Minkowksi distance, Hamming Distance are used to find the closest data. The mathematical formulation for the final prediction f_(K(x)) is as shown in Equation 2 (Bawa et al., 2024).

$$f_{K(x)} = \arg\max x_c \sum_{i=1}^{k} I\,(c = x_k) \quad 2$$

3.4.4. Support Vector Machines (SVM):

Support vector machines are one of the machine learning methods that can be used for both classification and regression. The aim of support vector machines is to find a hyperplane that optimally classifies data points in an n-dimensional space (or a space with n variables) (Pal, 2005). Support vector machines, which can perform well on small datasets, are robust to the overfitting problem. The kernel parameter used in this technique transforms the hyperplane into a high-dimensional space and allows complex and non-linear relationships to be analysed (Cortes & Vapnik, 1995). In support vector machines, the hyperplane is designed to cover as many data points as possible and the final prediction, denoted by the symbol f_s (x), is calculated according to Equation 3. In Equation 3, w is a weight vector representing the hyperplane coefficients (Bawa et al., 2024).

$$f_s(x) = \min(w, b)\frac{1}{2}\left||w|\right|^2 \quad (3)$$

3.4.5. Random Forest (RF):

The random forest method is one of the ensemble learning techniques based on the combination of multiple models (Misra et al., 2020). In this method, which can be used in both classification and regression analysis, data subsets randomly generated from the data set by bagging technique are trained in parallel with a large number of decision trees and the final decision is obtained by combining the predictions of each tree, as shown in Equation 4 (Bawa et al., 2024). The bagging technique allows the random forest method to work on small datasets, while its architecture based on ensemble learning avoids the problem of overfitting (Umoh et al., 2022). Focusing on reducing variance rather than bias, the random forest method is more robust to noise in the dataset (Srivastava et al., 2023). The mathematical formulation for the final estimate f_(R(x)) is as shown in Equation 4 (Bawa et al., 2024).

$$f_R(x) = major_{vote}(predict_1, predict_2, \ldots, predict_n) \quad (4)$$

3.4.6. Gradient Boosting (GB):

The Gradient Boosting method is one of the methods based on ensemble learning techniques such as the random forest method. The Gradient Boosting method, whose basic idea is to learn from errors, follows a recursive and sequential path that tries to improve the current estimator in small steps (Friedman, 2001). In other words, in this method, the error is calculated in each iteration after the first prediction and a new predictor is created for weak learners by focusing on the errors that occur in each iteration (Nie et al., 2021; Meiseles & Rokach, 2024). Thus, by combining a weak learner with the next learner, the error is significantly reduced in subsequent steps. The final prediction f_GB (x), labelled y_1 in the equation, is used to determine the errors r_1 of the training set. In the equation lr represents the learning rate..

$$r_1 = y_1 - \hat{y}_1 \quad (5)$$

$$f_{GB}(x) = y_1 + (\mathrm{lr} \times r_1) + (lr \times r_2) + \cdots + (lr \times r_n) \quad (6)$$

3.5. Performance Metrics

The reliability and effectiveness of a test depends on the strength of the model, which can be measured by the accuracy, recall, precision and F1 score of the system. The equations given below provide the statistics needed to measure the success rate of any proposed system.

3.5.1. Confusion Matrix

Confusion matrix is a matrix that summarises the performance of the machine learning model aiming at labelling or classification on the test data. As seen in Figure 3, it shows how many predictions are correct and incorrect for each class.

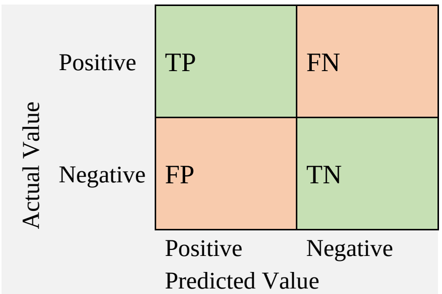

Figure 3: Confusion Matrix

True positives (TP) are when a positive data point is correctly predicted; true negatives (TN) are when a negative data point is correctly predicted. False positives (FP) occur when a positive data point is incorrectly predicted and false negatives (FN) occur when a negative data point is incorrectly predicted. In other words, successful predictions are referred to as true positives (TP) and true negatives (TN), while incorrect predictions are referred to as false positives (FP) and false negatives (FN). Classification problems are evaluated with metrics calculated according to these prediction results.

3.5.2. Accuracy

Accuracy is a metric that measures the frequency with which a machine learning model correctly predicts the outcome. The accuracy score is calculated as the ratio of the number of correct predictions to the total number of predictions. It is a useful metric when the accuracy of the model in general, rather than its ability to predict a particular class, is important. The calculation technique is shown in Equation 7.

$$Accuracy = \frac{T_P + T_N}{T_P + F_P + T_N + F_N} \tag{7}$$

3.5.3. Precision

Precision is the ratio of correctly classified positive examples to total positive examples. Precision is a metric that shows how accurately the machine learning model predicts the positive class. This ratio is useful when false positives have a high cost. The disadvantage of the model is that it does not take false negatives into account. The calculation technique is shown in Equation 8.

$$Precision = \frac{T_P}{T_P + F_P} \quad 8$$

3.5.4. Recall

Recall is the total number of correctly classified positive samples divided by the total number of positive samples. In other words, it includes true positives and false negative results. The higher the recall score on a scale from 0 to 1, the better it is considered to be, and a high recall score indicates that the class is correctly recognized. Recall is a useful metric when the cost of false negatives is high. However, recall does not take into account the cost of false positives. The calculation technique is shown in Equation 9.

$$Precision = \frac{T_P}{T_P + F_N} \quad 9$$

3.5.5. F1 Score

The F1 score, which is used to measure recall and precision scores at the same time, is the harmonic mean of precision and sensitivity criteria. It gives the opportunity to evaluate both criteria together. The calculation technique is shown in Equation 10.

$$f_1 score = \frac{2xT_P}{(2xT_P)+F_P + F_N} \quad 10$$

3.6. Data Sets of the Research

In this study, technical analysis indicators were calculated using daily and intraday price and volume data (opening, closing, lowest, highest, volume) of the companies in BIST 50. For the analysis of daily data, a total of 230.937 observations were obtained with a maximum of 30 years of historical data. For the analysis of hourly data, a total of 12.400 observations were obtained with hourly data for the last 60 days. Daily and hourly historical data including opening prices, closing prices, highest prices, lowest prices and volume data of BIST 50 stocks during the research period were obtained from https://finance.yahoo.com using the yfinance (https://pypi.org/project/yfinance/) module developed for Python. The technical indicators used as input variables and presented in Table 2 are used to predict stock directions. In the analysis, 80% of the data obtained for each firm is used for training and 20% is used for testing. Parameter optimization was performed for each model and the value sets defined for the models are presented in Table 4. As a result of the analysis, the prediction success of the machine learning algorithms is evaluated with the help of accuracy, precision, recall, and F1 score as performance evaluation metrics.

Table 3: Optimized Parameter Grids for Each Model

Model	Parameter	Values
ANN	hidden_layer_sizes	(5, 2), (10, 5), (50, 25)
	alpha	1e-05, 0.0001, 0.001
	solver	lbfgs
KNN	n_neighbors	5, 10, 20, 45
	weights	uniform, distance
BernoulliNB	alpha	0.0, 0.5, 1.0
	binarize	0.0, 0.5, 1.0
SVM	kernel	linear, rbf
	C	0.1, 1, 10
	gamma	scale, auto
RandomForest	n_estimators	100, 150, 200
	max_depth	None, 10, 20
GradientBoosting	n_estimators	50, 100, 150
	learning_rate	0.1, 1.0
	max_depth	1, 3, 5

4. RESULTS

Within the scope of this study, analyses were carried out on the basis of daily and daily hourly data, and the findings related to each level are reported under separate headings.

4.1. Using Technical Analysis Indicators in Forecasting with Long-Term Daily Data

This study investigates the performance of machine learning techniques, including Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting (GB), in predicting the direction of stock movements for daily basis. The accuracy, precision, recall, and F1 scores obtained for the test data set as a result of the analysis with daily data are presented in Table 4.

Table 4: Prediction Accuracy Scores of Machine Learning Methods (Daily)

	ANN				KNN				NB				SVM				RF				GB			
Firm	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**
AKBNK	0,47	0,38	0,48	0,47	0,72	0,72	0,72	0,72	0,57	0,51	0,58	0,57	0,55	0,50	0,54	0,55	0,91	0,91	0,91	0,91	0,70	0,70	0,70	0,70
ALARK	0,44	0,27	0,20	0,44	0,74	0,74	0,74	0,74	0,54	0,54	0,54	0,54	0,56	0,40	0,31	0,56	0,93	0,93	0,93	0,93	0,68	0,68	0,68	0,68
ALFAS	0,62	0,47	0,38	0,62	0,82	0,82	0,82	0,82	0,68	0,68	0,69	0,68	0,77	0,75	0,77	0,77	0,98	0,98	0,98	0,98	0,97	0,97	0,97	0,97
ARCLK	0,46	0,46	0,48	0,46	0,73	0,73	0,73	0,73	0,53	0,49	0,50	0,53	0,56	0,40	0,31	0,56	0,92	0,92	0,92	0,92	0,71	0,71	0,71	0,71
ASELS	0,43	0,27	0,40	0,43	0,73	0,73	0,73	0,73	0,54	0,53	0,53	0,54	0,57	0,50	0,56	0,57	0,92	0,92	0,92	0,92	0,72	0,72	0,72	0,72
ASTOR	0,39	0,22	0,15	0,39	0,88	0,88	0,88	0,88	0,69	0,68	0,68	0,69	0,84	0,84	0,85	0,84	0,98	0,98	0,98	0,98	0,88	0,88	0,89	0,88
BIMAS	0,37	0,20	0,77	0,37	0,68	0,67	0,67	0,68	0,58	0,58	0,58	0,58	0,63	0,49	0,40	0,63	0,91	0,91	0,91	0,91	0,69	0,68	0,68	0,69
BRSAN	0,48	0,41	0,49	0,48	0,69	0,69	0,69	0,69	0,54	0,49	0,54	0,54	0,53	0,37	0,28	0,53	0,92	0,92	0,93	0,92	0,72	0,72	0,72	0,72
CIMSA	0,47	0,32	0,54	0,47	0,73	0,73	0,73	0,73	0,56	0,51	0,57	0,56	0,53	0,37	0,28	0,53	0,93	0,93	0,93	0,93	0,74	0,74	0,75	0,74
CWENE	0,62	0,48	0,39	0,62	0,78	0,79	0,81	0,78	0,70	0,70	0,71	0,70	0,62	0,48	0,39	0,62	0,92	0,92	0,92	0,92	0,92	0,92	0,93	0,92
DOAS	0,42	0,25	0,17	0,42	0,74	0,74	0,74	0,74	0,57	0,57	0,57	0,57	0,58	0,43	0,34	0,58	0,92	0,92	0,92	0,92	0,76	0,76	0,76	0,76
DOHOL	0,47	0,33	0,34	0,47	0,72	0,72	0,72	0,72	0,51	0,51	0,51	0,51	0,53	0,47	0,57	0,53	0,91	0,91	0,91	0,91	0,74	0,74	0,74	0,74
EGEEN	0,43	0,26	0,19	0,43	0,74	0,74	0,74	0,74	0,51	0,51	0,51	0,51	0,57	0,41	0,32	0,57	0,92	0,92	0,92	0,92	0,71	0,70	0,71	0,71
EKGYO	0,47	0,30	0,22	0,47	0,72	0,72	0,72	0,72	0,51	0,51	0,51	0,51	0,57	0,52	0,59	0,57	0,91	0,91	0,91	0,91	0,77	0,77	0,77	0,77
ENJSA	0,33	0,16	0,11	0,33	0,72	0,71	0,71	0,72	0,66	0,59	0,60	0,66	0,67	0,54	0,45	0,67	0,93	0,93	0,93	0,93	0,85	0,84	0,85	0,85
ENKAI	0,40	0,26	0,44	0,40	0,71	0,70	0,71	0,71	0,56	0,56	0,57	0,56	0,60	0,46	0,76	0,60	0,91	0,91	0,91	0,91	0,72	0,72	0,72	0,72
EREGL	0,42	0,26	0,59	0,42	0,74	0,74	0,74	0,74	0,59	0,56	0,58	0,59	0,59	0,45	0,73	0,59	0,92	0,92	0,92	0,92	0,75	0,75	0,75	0,75
EUPWR	0,39	0,39	0,84	0,39	0,66	0,69	0,79	0,66	0,63	0,66	0,69	0,63	0,63	0,65	0,66	0,63	0,89	0,89	0,89	0,89	0,82	0,82	0,82	0,82
FROTO	0,41	0,24	0,76	0,41	0,69	0,67	0,68	0,69	0,61	0,53	0,61	0,61	0,60	0,45	0,76	0,60	0,92	0,92	0,92	0,92	0,72	0,71	0,72	0,72
GARAN	0,51	0,50	0,54	0,51	0,69	0,69	0,69	0,69	0,55	0,50	0,53	0,55	0,56	0,41	0,32	0,56	0,91	0,91	0,91	0,91	0,73	0,72	0,73	0,73
GESAN	0,52	0,50	0,78	0,52	0,81	0,79	0,82	0,81	0,56	0,55	0,55	0,56	0,68	0,55	0,46	0,68	0,92	0,92	0,92	0,92	0,93	0,93	0,94	0,93
GUBRF	0,46	0,29	0,21	0,46	0,72	0,72	0,72	0,72	0,56	0,56	0,56	0,56	0,54	0,38	0,29	0,54	0,91	0,91	0,91	0,91	0,73	0,73	0,74	0,73
HALKB	0,54	0,54	0,54	0,54	0,73	0,73	0,73	0,73	0,49	0,48	0,49	0,49	0,50	0,47	0,50	0,50	0,93	0,93	0,93	0,93	0,76	0,76	0,76	0,76
HEKTS	0,41	0,24	0,23	0,41	0,72	0,72	0,73	0,72	0,55	0,55	0,55	0,55	0,59	0,43	0,34	0,59	0,92	0,92	0,92	0,92	0,74	0,73	0,74	0,74
ISCTR	0,42	0,26	0,56	0,42	0,75	0,75	0,75	0,75	0,54	0,54	0,54	0,54	0,56	0,54	0,55	0,56	0,94	0,94	0,94	0,94	0,73	0,73	0,73	0,73
KCHOL	0,43	0,28	0,45	0,43	0,70	0,69	0,70	0,70	0,55	0,49	0,52	0,55	0,56	0,41	0,32	0,56	0,91	0,91	0,91	0,91	0,71	0,70	0,71	0,71
KONTR	0,45	0,27	0,20	0,45	0,75	0,75	0,75	0,75	0,51	0,41	0,42	0,51	0,64	0,59	0,68	0,64	0,91	0,91	0,92	0,91	0,89	0,89	0,89	0,89
KOZAA	0,47	0,35	0,57	0,47	0,70	0,71	0,71	0,70	0,53	0,53	0,53	0,53	0,55	0,39	0,30	0,55	0,92	0,92	0,92	0,92	0,74	0,74	0,74	0,74
KOZAL	0,44	0,27	0,19	0,44	0,75	0,75	0,75	0,75	0,50	0,50	0,49	0,50	0,57	0,43	0,71	0,57	0,91	0,91	0,91	0,91	0,78	0,78	0,78	0,78
KRDMD	0,46	0,31	0,41	0,46	0,71	0,71	0,71	0,71	0,55	0,55	0,55	0,55	0,55	0,46	0,55	0,55	0,92	0,92	0,92	0,92	0,71	0,71	0,71	0,71
MGROS	0,56	0,51	0,53	0,56	0,73	0,73	0,73	0,73	0,57	0,53	0,55	0,57	0,58	0,51	0,57	0,58	0,94	0,94	0,94	0,94	0,72	0,72	0,72	0,72
MIATK	0,53	0,53	0,56	0,53	0,70	0,67	0,73	0,70	0,55	0,55	0,56	0,55	0,62	0,54	0,73	0,62	0,90	0,90	0,90	0,90	0,89	0,89	0,89	0,89
ODAS	0,46	0,29	0,21	0,46	0,74	0,74	0,75	0,74	0,60	0,60	0,60	0,60	0,58	0,57	0,59	0,58	0,95	0,95	0,95	0,95	0,85	0,85	0,85	0,85
OYAKC	0,44	0,30	0,53	0,44	0,72	0,72	0,72	0,72	0,54	0,54	0,54	0,54	0,56	0,41	0,32	0,56	0,92	0,92	0,92	0,92	0,76	0,76	0,76	0,76
PETKM	0,45	0,28	0,20	0,45	0,70	0,70	0,70	0,70	0,57	0,56	0,56	0,57	0,55	0,39	0,30	0,55	0,92	0,92	0,92	0,92	0,75	0,75	0,75	0,75
PGSUS	0,44	0,41	0,47	0,44	0,74	0,74	0,74	0,74	0,49	0,49	0,49	0,49	0,60	0,58	0,59	0,60	0,92	0,92	0,92	0,92	0,78	0,78	0,78	0,78
SAHOL	0,47	0,33	0,51	0,47	0,71	0,70	0,71	0,71	0,53	0,47	0,51	0,53	0,54	0,38	0,29	0,54	0,92	0,92	0,92	0,92	0,72	0,72	0,73	0,72
SASA	0,47	0,31	0,41	0,47	0,68	0,68	0,68	0,68	0,53	0,53	0,53	0,53	0,55	0,55	0,55	0,55	0,92	0,92	0,92	0,92	0,72	0,72	0,72	0,72
SISE	0,46	0,30	0,56	0,46	0,70	0,69	0,70	0,70	0,57	0,52	0,58	0,57	0,54	0,38	0,29	0,54	0,92	0,92	0,93	0,92	0,73	0,72	0,73	0,73
SMRTG	0,45	0,27	0,20	0,45	0,76	0,76	0,76	0,76	0,58	0,58	0,58	0,58	0,66	0,66	0,67	0,66	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,96
TAVHL	0,41	0,25	0,76	0,41	0,74	0,73	0,74	0,74	0,57	0,45	0,47	0,57	0,61	0,55	0,60	0,61	0,89	0,89	0,89	0,89	0,74	0,73	0,74	0,74
TCELL	0,46	0,30	0,72	0,46	0,72	0,72	0,72	0,72	0,55	0,49	0,53	0,55	0,55	0,39	0,31	0,55	0,94	0,94	0,94	0,94	0,71	0,71	0,71	0,71
THYAO	0,45	0,28	0,20	0,45	0,72	0,72	0,72	0,72	0,52	0,53	0,53	0,52	0,56	0,50	0,55	0,56	0,91	0,91	0,91	0,91	0,71	0,71	0,71	0,71
TOASO	0,41	0,25	0,69	0,41	0,74	0,74	0,74	0,74	0,52	0,52	0,51	0,52	0,59	0,44	0,35	0,59	0,92	0,92	0,92	0,92	0,70	0,69	0,70	0,70
TTKOM	0,42	0,25	0,18	0,42	0,72	0,72	0,72	0,72	0,56	0,55	0,55	0,56	0,58	0,42	0,33	0,58	0,91	0,91	0,91	0,91	0,76	0,76	0,76	0,76
TUPRS	0,42	0,25	0,56	0,42	0,71	0,70	0,70	0,71	0,58	0,47	0,52	0,58	0,59	0,46	0,58	0,59	0,92	0,92	0,92	0,92	0,72	0,71	0,72	0,72
ULKER	0,45	0,31	0,57	0,45	0,72	0,72	0,73	0,72	0,56	0,56	0,56	0,56	0,56	0,40	0,31	0,56	0,92	0,92	0,92	0,92	0,75	0,75	0,75	0,75
VESTL	0,51	0,35	0,65	0,51	0,76	0,76	0,76	0,76	0,52	0,52	0,52	0,52	0,54	0,51	0,54	0,54	0,92	0,92	0,92	0,92	0,73	0,73	0,73	0,73
YKBNK	0,47	0,32	0,45	0,47	0,68	0,68	0,68	0,68	0,55	0,53	0,54	0,55	0,53	0,36	0,28	0,53	0,92	0,92	0,92	0,92	0,70	0,70	0,70	0,70
ZOREN	0,51	0,44	0,50	0,51	0,72	0,72	0,72	0,72	0,53	0,53	0,53	0,53	0,55	0,48	0,60	0,55	0,92	0,92	0,92	0,92	0,69	0,69	0,69	0,69

In an analysis using daily frequency data to predict the directional movement of stocks listed in Borsa Istanbul, it is revealed that various machine learning models exhibit different performances. Within the framework of this analysis, widely recognized algorithms such as ANN, KNN, NB, SVM, RF, and GB are trained using daily data obtained from technical indicators of stocks.

In the analysis with daily data, the most consistently high performing models are again RF and GB. In particular, the RF model achieved significantly higher accuracy rates in all companies compared to other methods. For example, in ALFAS, ASTOR and ODAS stocks, the RF method achieved very high accuracy rates of 98%, 98% and 95%, respectively. This shows that the RF algorithm is able to predict market movements on a daily basis quite successfully.

The GB method, on the other hand, performed strongly for many companies but generally lagged behind RF. For example, the 97% accuracy rate of the GB model for ALFAS stock and 89% accuracy rate for KONTR and MIATK stocks show that GB is a solid alternative but cannot achieve the consistency of RF.

The KNN algorithm produced moderately to highly successful results for many companies at daily frequency. For example, in GESAN stock, it showed high performance with an accuracy of 81%, while in general, it showed moderate consistency with accuracy ranging from 68% to 82%. This shows that KNN can be used to predict daily price movements, but its stability decreases in high volatility situations.

SVM and NB algorithms generally performed poorly to moderately on daily data. In particular, the SVM model performed very poorly for some stocks on a daily basis, with low accuracy rates of only 56% for ALARK and 56% for ARCLK. Similarly, the NB algorithm often remained in the 50-60% band, indicating that it is not a strong model at daily frequency.

The ANN algorithm showed generally poor results on a daily basis. For example, it achieved only 33% accuracy for ENJSA stock, clearly showing that its effectiveness on daily data is quite limited. Similar poor performances were observed for stocks in different sectors.

In conclusion, the superiority of ensemble methods such as RF and GB over other methods in predicting the direction of price movements based on technical indicators at the daily level is clearly evident. In particular, the RF model has been identified as the most powerful method in daily analysis in terms of both consistency and high predictive power. It is understood that other methods may be an alternative in certain situations or for certain stocks, but they exhibit limited effectiveness under general market conditions. These results align with existing literature findings that highlight the efficacy of machine learning approaches in predicting stock price movements (Kim, 2003; Weng et al., 2017; Patel et al., 2015; Lee et al., 2021).

4.2. Using Technical Analysis Indicators in Forecasting with Short-Term Intraday Hourly Data

The study also investigates the performance of machine learning algorithms—such as Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting (GB)—in predicting the directional movements of stocks for intraday transactions. The accuracy, precision, recall, and F1 scores obtained for the test data set as a result of the analysis with hourly data are presented in Table 5.

Table 5: Prediction Accuracy Scores of Machine Learning Methods (Intraday)

	ANN				KNN				NB				SVM				RF				GB			
Firm	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**	**Acc**	**F1**	**Prec**	**Rec**
AKBNK	0,28	0,12	0,08	0,28	0,72	0,71	0,71	0,72	0,58	0,60	0,62	0,58	0,70	0,71	0,72	0,70	0,90	0,90	0,90	0,90	0,84	0,85	0,88	0,84
ALARK	0,60	0,50	0,77	0,60	0,78	0,78	0,78	0,78	0,68	0,66	0,70	0,68	0,78	0,78	0,78	0,78	0,98	0,98	0,98	0,98	0,94	0,94	0,95	0,94
ALFAS	0,48	0,44	0,41	0,48	0,74	0,75	0,76	0,74	0,72	0,71	0,71	0,72	0,88	0,88	0,88	0,88	0,94	0,94	0,94	0,94	0,92	0,92	0,93	0,92
ARCLK	0,54	0,45	0,77	0,54	0,48	0,48	0,48	0,48	0,54	0,53	0,56	0,54	0,62	0,62	0,63	0,62	0,84	0,84	0,85	0,84	0,86	0,86	0,87	0,86
ASELS	0,44	0,27	0,19	0,44	0,80	0,80	0,80	0,80	0,58	0,58	0,58	0,58	0,84	0,84	0,86	0,84	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,96
ASTOR	0,66	0,61	0,64	0,66	0,68	0,68	0,69	0,68	0,58	0,59	0,63	0,58	0,72	0,71	0,71	0,72	0,96	0,96	0,96	0,96	0,94	0,94	0,94	0,94
BIMAS	0,60	0,45	0,36	0,60	0,74	0,74	0,81	0,74	0,68	0,68	0,69	0,68	0,80	0,80	0,83	0,80	0,96	0,96	0,96	0,96	0,88	0,88	0,89	0,88
BRSAN	0,38	0,21	0,14	0,38	0,82	0,82	0,84	0,82	0,56	0,57	0,58	0,56	0,72	0,72	0,72	0,72	0,96	0,96	0,96	0,96	0,92	0,92	0,92	0,92
CIMSA	0,66	0,52	0,44	0,66	0,62	0,62	0,75	0,62	0,48	0,49	0,56	0,48	0,70	0,71	0,73	0,70	0,86	0,86	0,87	0,86	0,88	0,88	0,88	0,88
CWENE	0,72	0,60	0,52	0,72	0,78	0,77	0,77	0,78	0,78	0,77	0,77	0,78	0,84	0,84	0,84	0,84	0,98	0,98	0,98	0,98	0,96	0,96	0,97	0,96
DOAS	0,50	0,33	0,25	0,50	0,72	0,72	0,72	0,72	0,74	0,74	0,74	0,74	0,74	0,74	0,75	0,74	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88
DOHOL	0,58	0,58	0,58	0,58	0,72	0,70	0,78	0,72	0,60	0,60	0,60	0,60	0,72	0,70	0,78	0,72	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,96
EGEEN	0,38	0,21	0,14	0,38	0,82	0,82	0,83	0,82	0,48	0,49	0,51	0,48	0,74	0,74	0,75	0,74	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88
EKGYO	0,56	0,40	0,31	0,56	0,62	0,62	0,64	0,62	0,52	0,51	0,51	0,52	0,68	0,68	0,68	0,68	0,90	0,90	0,92	0,90	0,98	0,98	0,98	0,98
ENJSA	0,52	0,44	0,45	0,52	0,68	0,68	0,68	0,68	0,64	0,64	0,66	0,64	0,64	0,64	0,67	0,64	0,90	0,90	0,92	0,90	0,94	0,94	0,95	0,94
ENKAI	0,56	0,48	0,60	0,56	0,68	0,67	0,72	0,68	0,64	0,64	0,65	0,64	0,62	0,59	0,70	0,62	0,94	0,94	0,95	0,94	0,92	0,92	0,92	0,92
EREGL	0,42	0,42	0,42	0,42	0,68	0,67	0,70	0,68	0,60	0,60	0,60	0,60	0,58	0,56	0,60	0,58	0,90	0,90	0,90	0,90	0,88	0,88	0,88	0,88
EUPWR	0,58	0,43	0,34	0,58	0,88	0,88	0,88	0,88	0,62	0,62	0,62	0,62	0,84	0,84	0,88	0,84	0,96	0,96	0,96	0,96	0,90	0,90	0,91	0,90
FROTO	0,48	0,37	0,38	0,48	0,68	0,68	0,68	0,68	0,70	0,70	0,71	0,70	0,80	0,80	0,82	0,80	0,96	0,96	0,96	0,96	0,92	0,92	0,92	0,92
GARAN	0,40	0,23	0,16	0,40	0,60	0,57	0,58	0,60	0,64	0,64	0,65	0,64	0,60	0,45	0,36	0,60	0,94	0,94	0,95	0,94	0,88	0,88	0,88	0,88
GESAN	0,48	0,31	0,23	0,48	0,64	0,63	0,65	0,64	0,60	0,60	0,60	0,60	0,72	0,72	0,72	0,72	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,96
GUBRF	0,44	0,36	0,79	0,44	0,72	0,72	0,71	0,72	0,60	0,60	0,60	0,60	0,72	0,72	0,72	0,72	0,94	0,94	0,94	0,94	0,90	0,90	0,91	0,90
HALKB	0,18	0,05	0,03	0,18	0,54	0,59	0,73	0,54	0,40	0,47	0,63	0,40	0,82	0,74	0,67	0,82	0,80	0,80	0,80	0,80	0,88	0,88	0,89	0,88
HEKTS	0,56	0,52	0,51	0,56	0,68	0,68	0,68	0,68	0,70	0,70	0,70	0,70	0,82	0,82	0,84	0,82	0,90	0,90	0,92	0,90	0,84	0,84	0,85	0,84
ISCTR	0,36	0,19	0,13	0,36	0,78	0,78	0,78	0,78	0,60	0,61	0,63	0,60	0,76	0,76	0,76	0,76	0,94	0,94	0,95	0,94	0,94	0,94	0,94	0,94
KCHOL	0,50	0,49	0,49	0,50	0,68	0,68	0,69	0,68	0,70	0,70	0,70	0,70	0,76	0,76	0,77	0,76	0,92	0,92	0,93	0,92	0,94	0,94	0,94	0,94
KONTR	0,60	0,61	0,66	0,60	0,68	0,64	0,65	0,68	0,54	0,56	0,60	0,54	0,82	0,80	0,83	0,82	0,96	0,96	0,96	0,96	0,94	0,94	0,94	0,94
KOZAA	0,52	0,49	0,50	0,52	0,60	0,57	0,69	0,60	0,74	0,74	0,74	0,74	0,50	0,37	0,76	0,50	0,92	0,92	0,93	0,92	0,96	0,96	0,96	0,96
KOZAL	0,56	0,48	0,54	0,56	0,72	0,72	0,72	0,72	0,72	0,72	0,72	0,72	0,64	0,62	0,72	0,64	0,94	0,94	0,94	0,94	0,90	0,90	0,90	0,90
KRDMD	0,42	0,32	0,41	0,42	0,58	0,47	0,62	0,58	0,66	0,66	0,67	0,66	0,56	0,40	0,31	0,56	1,00	1,00	1,00	1,00	0,98	0,98	0,98	0,98
MGROS	0,54	0,40	0,76	0,54	0,70	0,70	0,70	0,70	0,50	0,50	0,50	0,50	0,74	0,73	0,77	0,74	0,92	0,92	0,92	0,92	0,90	0,90	0,90	0,90
MIATK	0,68	0,62	0,80	0,68	0,66	0,66	0,66	0,66	0,70	0,70	0,70	0,70	0,82	0,82	0,82	0,82	0,92	0,92	0,93	0,92	0,94	0,94	0,95	0,94
ODAS	0,60	0,45	0,36	0,60	0,80	0,80	0,84	0,80	0,82	0,82	0,82	0,82	0,84	0,84	0,87	0,84	0,98	0,98	0,98	0,98	0,98	0,98	0,98	0,98
OYAKC	0,30	0,14	0,09	0,30	0,70	0,71	0,73	0,70	0,64	0,66	0,72	0,64	0,70	0,58	0,49	0,70	0,90	0,90	0,90	0,90	0,82	0,83	0,85	0,82
PETKM	0,42	0,42	0,42	0,42	0,80	0,80	0,80	0,80	0,54	0,54	0,55	0,54	0,82	0,82	0,82	0,82	0,82	0,82	0,82	0,82	0,86	0,86	0,86	0,86
PGSUS	0,40	0,23	0,16	0,40	0,76	0,75	0,76	0,76	0,62	0,52	0,64	0,62	0,60	0,45	0,36	0,60	0,94	0,94	0,94	0,94	0,98	0,98	0,98	0,98
SAHOL	0,48	0,31	0,23	0,48	0,62	0,55	0,78	0,62	0,66	0,66	0,66	0,66	0,52	0,36	0,27	0,52	0,92	0,92	0,93	0,92	0,96	0,96	0,96	0,96
SASA	0,46	0,46	0,45	0,46	0,64	0,65	0,67	0,64	0,56	0,55	0,55	0,56	0,76	0,75	0,76	0,76	0,92	0,92	0,92	0,92	0,88	0,88	0,88	0,88
SISE	0,68	0,58	0,63	0,68	0,70	0,66	0,67	0,70	0,58	0,59	0,64	0,58	0,80	0,78	0,81	0,80	0,96	0,96	0,96	0,96	0,96	0,96	0,96	0,96
SMRTG	0,50	0,41	0,35	0,50	0,74	0,74	0,76	0,74	0,70	0,70	0,70	0,70	0,64	0,63	0,63	0,64	0,94	0,94	0,95	0,94	0,92	0,92	0,92	0,92
TAVHL	0,58	0,58	0,59	0,58	0,64	0,65	0,69	0,64	0,60	0,59	0,59	0,60	0,72	0,72	0,74	0,72	0,92	0,92	0,92	0,92	0,82	0,82	0,84	0,82
TCELL	0,52	0,36	0,27	0,52	0,62	0,62	0,62	0,62	0,64	0,64	0,64	0,64	0,60	0,59	0,61	0,60	0,78	0,78	0,78	0,78	0,84	0,84	0,84	0,84
THYAO	0,48	0,31	0,23	0,48	0,56	0,46	0,64	0,56	0,54	0,53	0,54	0,54	0,52	0,36	0,27	0,52	0,92	0,92	0,93	0,92	0,90	0,90	0,91	0,90
TOASO	0,54	0,51	0,59	0,54	0,66	0,64	0,73	0,66	0,48	0,48	0,48	0,48	0,66	0,64	0,73	0,66	0,84	0,84	0,84	0,84	0,82	0,82	0,82	0,82
TTKOM	0,50	0,33	0,25	0,50	0,70	0,68	0,75	0,70	0,64	0,64	0,64	0,64	0,66	0,66	0,66	0,66	0,84	0,84	0,84	0,84	0,84	0,84	0,84	0,84
TUPRS	0,60	0,45	0,36	0,60	0,62	0,61	0,61	0,62	0,54	0,54	0,54	0,54	0,62	0,62	0,63	0,62	0,94	0,94	0,94	0,94	0,94	0,94	0,94	0,94
ULKER	0,52	0,36	0,27	0,52	0,76	0,76	0,76	0,76	0,60	0,60	0,60	0,60	0,76	0,76	0,76	0,76	0,92	0,92	0,92	0,92	0,92	0,92	0,92	0,92
VESTL	0,68	0,55	0,46	0,68	0,70	0,69	0,69	0,70	0,72	0,72	0,72	0,72	0,62	0,55	0,52	0,62	0,86	0,86	0,87	0,86	0,82	0,83	0,86	0,82
YKBNK	0,48	0,31	0,23	0,48	0,78	0,78	0,81	0,78	0,64	0,63	0,66	0,64	0,84	0,84	0,86	0,84	0,94	0,94	0,94	0,94	0,92	0,92	0,92	0,92
ZOREN	0,68	0,55	0,46	0,68	0,66	0,59	0,60	0,66	0,74	0,70	0,73	0,74	0,72	0,64	0,80	0,72	0,98	0,98	0,98	0,98	0,98	0,98	0,98	0,98

The direction of the prices of stocks traded in Borsa Istanbul in 1-hour periods are predicted by ANN, KNN, NB, SVM, RF and GB algorithms. In contrast to daily analysis, the performance of these methods is likely to decrease due to the increased volatility associated with intraday data. However, when examining Table 5, the performance of RF and GB algorithms compared to other models is remarkable. For example, on stocks such as ODAS and CWENE, both the RF and GB models performed very well, achieving 98% accuracy rates. This observation implies that tree-based ensemble methodologies are also good at capturing the complex high-frequency fluctuations found in intraday data.

The performance of the ANN algorithm has often been inadequate in analyzing intraday data. For example, the ANN model achieved an accuracy score of only 18% with respect to HALKB stocks and exhibited low values in other performance measures (precision, recall and F1 scores). This finding suggests that the effectiveness of the ANN model in the context of intraday trading is significantly limited.

KNN and SVM models performed more moderately in analyzing intraday data. For example, the lowest classification performance of the KNN model was 48% accuracy for ARCLK stock. These findings suggest that KNN may not have the flexibility to withstand market volatility in intraday trading.

The NB model, on the other hand, showed moderate consistency across various stocks, but its performance was lower in terms of overall performance compared to ensemble models such as RF and GB. This was particularly evident for stocks such as BRSAN (56% accuracy) and HALKB (40% accuracy) where performance limitations were clearly observable.

In conclusion, the most effective methodologies for predicting price movement directions using technical analysis indicators at the intraday level are tree-based ensemble models, RF and GB. These methodologies appear to offer distinct advantages in capturing and predicting short-term market fluctuations. These findings underscore the robustness of the RF and GB algorithms in intraday prediction tasks and highlight its superiority over alternative machine learning methods in predicting stock price directions within the BIST 50 Index.

5. CONCLUSION AND EVALUATION

This study aims to predict the stock movement directions of companies in the BIST 50 index using machine learning classification algorithms. It compares the performance of various algorithms to identify the most effective forecaster. The analysis consists of two main parts: evaluating the predictive power of technical analysis over thirty years of daily data for long-term investments and evaluating its success in intraday trading using 60 days of hourly data. For these predictions, algorithms such as Artificial Neural Networks, K-Nearest Neighbors, Support Vector Machines, Naive Bayes, Random Forest and Gradient Boosting were used.

According to the results obtained from the analysis, RF and GB methods based on ensemble learning were found to be the best methods for predicting the direction of stock prices. Both the fact that different machine learning algorithms are more successful for different stocks and that the prediction performance of each stock is different indicates that stocks have unique characteristics.

The findings of the analysis reveal that machines can successfully predict the direction of stocks at both daily and intraday levels using technical analysis indicators. In this context, it indicates that investors can develop investment strategies using GB and RF algorithms based on ensemble learning. The fact that the direction of stocks can be predicted with great accuracy by machines trained with technical indicators may allow investors to make more advantageous decisions in the trade-off between profitability and risk. Moreover, in the context of financial artificial intelligence, it is clear that machine learning models developed with technical analysis indicators will bring a technical analysis-based capability to algorithmic financial transactions.

In light of the findings of this study, there are some limitations. In particular, the absence of deep learning methods among the machine learning methods compared is one of the important limitations. It can also be tested for shorter time frames such as minutes, five minutes, fifteen minutes in intraday analysis. In addition, analysis of candlestick charts can also be included in technical indicators.

In future studies, deep learning algorithms can be included in machine learning methods. In addition, intraday analyses can be tested for shorter time frames such as minutes, five minutes, fifteen minutes and strategies can be developed accordingly. Finally, technical indicators obtained from candlestick analysis can be included in the input variables.

Ethical Declaration

In this study, all the rules stated in the “Higher Education Institutions Scientific Research (Türkiye) and Publication Ethics Directive” were followed.

Ethics Committee

The author declare that the research is one of the studies that does not require ethical committee approval.

Conflict of Interest and Funding

No conflict of interest and funding has been declared by the authors.

REFERENCES

Abarbanell, J. S., & Bushee, B. J. (1997). Fundamental analysis, future earnings, and stock prices. *Journal of accounting research*, *35*(1), 1-24.

Agrawal, M., Khan, A. U., & Shukla, P. K. (2019). Stock indices price prediction based on technical indicators using deep learning model. *International Journal on Emerging Technologies*, *10*(2), 186-194.

Aït-Sahalia, Y., & Xiu, D. (2019). Principal component analysis of high-frequency data. *Journal of the american statistical association, 114*(525), 287-303.

Albahli, S., Nazir, T., Nawaz, M., & Irtaza, A. (2023). An improved DenseNet model for prediction of stock market using stock technical indicators. *Expert Systems with Applications, 232*, 120903.

Ayala, J., García-Torres, M., Noguera, J. L. V., Gómez-Vela, F., & Divina, F. (2021). Technical analysis strategy optimization using a machine learning approach in stock market indices. *Knowledge-Based Systems*, *225*, 107119.

Ayyildiz, N., & Iskenderoglu, O. (2024). How effective is machine learning in stock market predictions?. *Heliyon*, *10*(2).

Ballings, M., Van den Poel, D., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert systems with Applications*, *42*(20), 7046-7056.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. Handbook of the Economics of Finance, 1, 1053-1128.

Bawa, P., Kadyan, V., Mantri, A., & Vardhan, H. (2024). Investigating multiclass autism spectrum disorder classification using machine learning techniques. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, *8*, 100602.

Bessembinder, H., & Chan, K. (1995). The profitability of technical trading rules in the Asian stock markets. *Pacific-basin finance journal*, *3*(2-3), 257-284.

Beyer, K., Goldstein, J., Ramakrishnan, R., & Shaft, U. (1999). When is "nearest neighbor" meaningful?. In *Database Theory—ICDT'99: 7th International Conference Jerusalem, Israel, January 10–12, 1999 Proceedings 7* (pp. 217-235). Springer Berlin Heidelberg.

Bhatia, N. (2010). Survey of nearest neighbor techniques. *arXiv preprint arXiv:1007.0085*.

Bisoi, R., & Dash, P. K. (2014). A hybrid evolutionary dynamic neural network for stock market trend analysis and prediction using unscented Kalman filter. *Applied Soft Computing*, *19*, 41-56.

Bordino, I., Battiston, S., Caldarelli, G., Cristelli, M., Ukkonen, A., & Weber, I. (2012). Web search queries can predict stock market volumes. *PloS one*, *7*(7), e40014.

Borsa İstanbul. (2024). *BIST 50 index detail*. Retrieved July 5, 2024, from https://www.borsaistanbul.com/en/index-detail/6/bist-50

Chart Formations. (2024, July 5). *Cycle indicator*. https://www.chart-formations.com/indicators/cycle

Cootner, P. H. (1964). *The random character of stock market prices*. MIT Press.

Copeland, B.J.. "artificial intelligence". Encyclopedia Britannica, 5 Jun. 2024, https://www.britannica.com/technology/artificial-intelligence. Accessed 6 June 2024.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine learning*, *20*, 273-297.

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. *Handbooks in operations research and management science*, *9*, 385-410.

De Oliveira, F. A., Nobre, C. N., & Zárate, L. E. (2013). Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index–Case study of PETR4, Petrobras, Brazil. *Expert systems with applications*, *40*(18), 7596-7606.

Fama, E. F. (1965a). The behavior of stock-market prices. *The journal of Business*, *38*(1), 34-105.

Fama, E. F. (1965b). Random Walks in Stock Market Prices. *Financial Analysts Journal*, *21*(5), 55–59. http://www.jstor.org/stable/4469865

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417. https://doi.org/10.2307/2325486

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417. https://doi.org/10.2307/2325486

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. The Annals of Statistics, 29(5), 1189-1232.

Goutte, S., Le, H. V., Liu, F., & Von Mettenheim, H. J. (2023). Deep learning and technical analysis in cryptocurrency market. *Finance Research Letters*, *54*, 103809.

Hale, B., (2023). The Only Technical Analysis Book You Will Ever Need: A Must-Have Charting Manual for Traders and Investors. Independently published.

Haykin, S. (1998). *Neural networks: a comprehensive foundation*. Prentice Hall PTR.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, *7*, 133-159.

Hou, K., Karolyi, G. A., & Kho, B. C. (2011). What factors drive global stock returns?. *The Review of Financial Studies*, *24*(8), 2527-2574.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260.

Kahn, M. N. (2009). *Technical analysis plain and simple: Charting the markets in your language*. FT Press.

Kamara, A. F., Chen, E., & Pan, Z. (2022). An ensemble of a boosted hybrid of deep learning models and technical analysis for forecasting stock prices. *Information Sciences*, *594*, 1-19.

Khan, A. U., Bandopadhyaya, T. K., & Sharma, S. (2008, July). Comparisons of stock rates prediction accuracy using different technical indicators with backpropagation neural network and genetic algorithm based backpropagation neural network. In *2008 First International Conference on Emerging Trends in Engineering and Technology* (pp. 575-580). IEEE.

Khaniki, M. A. L., & Manthouri, M. (2024). Enhancing Price Prediction in Cryptocurrency Using Transformer Neural Network and Technical Indicators. *arXiv preprint arXiv:2403.03606*.

Kheradyar, S., Ibrahim, I., & Nor, F. M. (2011). Stock return predictability with financial ratios. *International Journal of Trade, Economics and Finance*, *2*(5), 391.

Kim, K. J. (2003). Financial time series forecasting using support vector machines. *Neurocomputing*, *55*(1-2), 307-319.

Laaksonen, J., & Oja, E. (1996, June). Classification with learning k-nearest neighbors. In *Proceedings of international conference on neural networks (ICNN'96)* (Vol. 3, pp. 1480-1483). IEEE.

Lee, J. W., Park, J., Jangmin, O., Lee, J., & Hong, E. (2007). A multiagent approach to $ q $-learning for daily stock trading. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *37*(6), 864-877.

Lee, M. C., Chang, J. W., Hung, J. C., & Chen, B. L. (2021). Exploring the effectiveness of deep neural networks with technical analysis applied to stock market prediction. *Computer Science and Information Systems*, *18*(2), 401-418.

Li, Q., Wang, T., Gong, Q., Chen, Y., Lin, Z., & Song, S. K. (2014a). Media-aware quantitative trading based on public Web information. *Decision support systems*, *61*, 93-105.

Li, X., Huang, X., Deng, X., & Zhu, S. (2014b). Enhancing quantitative intra-day stock return prediction by integrating both market news and stock prices information. *Neurocomputing*, *142*, 228-238.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

Malkiel, B. G. (1973). *A Random Walk Down Wall Street: Including A Life-Cycle Guide To Personal Investing*. W.W. Norton & Company, Inc.

Meiseles, A., & Rokach, L. (2024). Iterative Feature eXclusion (IFX): Mitigating feature starvation in gradient boosted decision trees. *Knowledge-Based Systems*, 111546.

Misra, S., Li, H., & He, J. (2020). Noninvasive fracture characterization based on the classification of sonic wave travel times. *Machine learning for subsurface characterization*, *4*, 243-287.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*(4), 768–783. https://doi.org/10.2307/1910098

Murphy, J. J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. Penguin.

Nie, P., Roccotelli, M., Fanti, M. P., Ming, Z., & Li, Z. (2021). Prediction of home energy consumption based on gradient boosting regression tree. *Energy Reports*, *7*, 1246-1255.

Ou, J. A., & Penman, S. H. (1989). Financial statement analysis and the prediction of stock returns. *Journal of accounting and economics*, *11*(4), 295-329.

Pal, M. (2005). Random forest classifier for remote sensing classification. *International journal of remote sensing*, *26*(1), 217-222.

Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert systems with applications*, *42*(1), 259-268.

Peng, Y., Albuquerque, P. H. M., Kimura, H., & Saavedra, C. A. P. B. (2021). Feature selection and deep neural networks for stock price direction forecasting using technical analysis indicators. *Machine Learning with Applications*, *5*, 100060.

Pxardeshi, Y. K., & Kale, P. (2021, July). Technical analysis indicators in stock market using machine learning: A comparative analysis. In *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE.

Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Systems with Applications*, *42*(6), 3234-3241.

Rockefeller, B. (2019). *Technical analysis for dummies*. John Wiley & Sons.

Rodríguez-González, A., García-Crespo, Á., Colomo-Palacios, R., Iglesias, F. G., & Gómez-Berbís, J. M. (2011). CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator. *Expert systems with Applications*, *38*(9), 11489-11500.

Russell, S. J., & Norvig, P. (2021). *Artificial intelligence a modern approach* (4rd ed.). London

Saghiri, A. M., Vahidipour, S. M., Jabbarpour, M. R., Sookhak, M., & Forestiero, A. (2022). A survey of artificial intelligence challenges: Analyzing the definitions, relationships, and evolutions. *Applied sciences*, *12*(8), 4054.

Sezer, O. B., Ozbayoglu, M., & Dogdu, E. (2017). A deep neural-network based stock trading system based on evolutionary optimized technical analysis parameters. *Procedia computer science*, *114*, 473-480.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Shefrin, H. (2002). *Beyond greed and fear: Understanding behavioral finance and the psychology of investing*. Oxford University Press.

Shiller, R. J. (2015). Irrational exuberance: Revised and expanded third edition. In *Irrational exuberance*. Princeton university press.

Srivastava, R., Kumar, S., & Kumar, B. (2023). Classification model of machine learning for medical data analysis. In *Statistical Modeling in Machine Learning* (pp. 111-132). Academic Press.

Sun, A., Lachanski, M., & Fabozzi, F. J. (2016). Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction. *International Review of Financial Analysis*, *48*, 272-281.

Sureshkumar, K. K., & Elango, N. M. (2011). An efficient approach to forecast Indian stock market price and their performance analysis. *International Journal of Computer Applications*, *34*(5), 44-49.

Teixeira, L. A., & De Oliveira, A. L. I. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert systems with applications*, *37*(10), 6885-6890.

Thaler, R. H. (2015). *Misbehaving: The making of behavioral economics*. WW Norton & Company.

Treynor, Jack L. (1962). *Toward a Theory of Market Value of Risky Assets*. Unpublished manuscript. A final version was published in 1999, in Asset Pricing and Portfolio Performance: Models, Strategy and Performance Metrics. Robert A. Korajczyk (editor) London: Risk Books, pp. 15–22.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), 1124-1131.

Umoh, U. A., Eyoh, I. J., Murugesan, V. S., & Nyoho, E. E. (2022). Fuzzy-machine learning models for the prediction of fire outbreaks: A comparative analysis. In *Artificial Intelligence and Machine Learning for EDGE Computing* (pp. 207-233). Academic Press.

Vapnik, V. (1995). The nature of statistical learning theory. Springer Science & Business Media.

Wei, L. Y., Chen, T. L., & Ho, T. H. (2011). A hybrid model based on adaptive-network-based fuzzy inference system to forecast Taiwan stock market. *Expert Systems with Applications*, *38*(11), 13625-13631.

Weng, B., Ahmed, M. A., & Megahed, F. M. (2017). Stock market one-day ahead movement prediction using disparate data sources. *Expert Systems with Applications*, *79*, 153-163.

Wilder, J. W. (1978). *New concepts in technical trading systems*. Greensboro, NC.

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through twitter "I hope it is not as bad as I fear". *Procedia-Social and Behavioral Sciences*, *26*, 55-62.

Zhang, Y., & Wang, J. (2016). K-nearest neighbors and a kernel density estimator for GEFCom2014 probabilistic wind power forecasting. *International Journal of forecasting*, *32*(3), 1074-1080.