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Integrating Technical Indicators, Financial Ratios, and Machine Learning: Evidence from Turkish Holding and Investment Companies

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Abstract. This study develops predictive models for the closing prices of stocks belonging to the Financial Institutions / Holdings and Investment Companies sector within the BIST 100 index, covering the period from 1993 to 2023. Using a dataset of 35 variables—including fundamental metrics, technical indicators, and financial ratios—the study applies advanced machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Particle Swarm Optimization (PSO)-enhanced hybrid models. Model performance was evaluated using R^2, Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The PSO-SVM hybrid model delivered the strongest results, with R^2 values exceeding 0.97 and MAPE as low as 3.21%. The SVM model demonstrated superior accuracy, achieving R^2 of 0.9989 and MAPE of 1.19%. In contrast, the ANN model yielded moderate outcomes, with R^2 around 0.91 and MAPE values ranging from 7.82% to 13.87%. These findings highlight the effectiveness of integrating fundamental and technical indicators with advanced machine learning, while also providing sector-specific insights into the financial and operational dynamics of holding and investment companies.

Keywords. machine learning, stock price prediction, financial markets, behavioral finance

Introduction

In today's fast-paced and ever-evolving financial landscape, making informed investment choices is essential for achieving financial success. For investors, the capacity to accurately forecast stock prices can result in considerable financial rewards. By utilizing a range of tools, strategies, and insights, investors can make well-informed decisions that are aligned with their financial goals and aspirations.

The stock exchange is a crucial component of the global financial system. It serves as the platform for the buying, selling, and issuance of shares in publicly traded companies. By offering shares to investors, companies can raise capital and provide ownership stakes, enabling individuals and institutions to participate in the ownership and potential profits of these firms. Additionally, the stock exchange plays a significant role in fostering economic growth, capital formation, and wealth creation by providing companies with the necessary funding for expansion and innovation. A variety of factors—including economic indicators, corporate performance, geopolitical events, and investor sentiment—affect activities within the stock market (Niszczota and Białek, 2021: 1-6).

The direction of the stock index pertains to the movement of the price index and the anticipated fluctuations of the stock index in the future. Predicting this direction is crucial, as it greatly impacts an investor's decision to buy or sell a financial instrument. Accurate forecasting of stock index trends enables investors to capitalize on opportunities for profit within the stock market. Thus, precise predictions of stock price index trends can be exceedingly beneficial for investors.

The global interconnectedness of stock markets facilitates the observation of stock return movements across various countries and regions. This integration allows investors to diversify their portfolios internationally, seize opportunities in different markets, and mitigate their risks (Salameh and Ahmad, 2022: 1-7). Furthermore, technological advancements have transformed stock trading, making it more accessible and efficient for investors to engage in the market. The increasing use of machine learning algorithms to predict stock prices and detect market manipulation further enhances the decision-making process for investors (Tarigan et al., 2021: 151-158).

In the context of predicting stock closing values, the Efficient Market Hypothesis (EMH) posits that stock prices quickly adjust to reflect new information, making it challenging to consistently and accurately forecast these prices (Huang, 2023: 892). Nonetheless, research has investigated the potential of ARIMA models for stock price prediction, as highlighted in the "Stock Value Prediction" literature. These models address the challenges posed by the efficient market hypothesis in forecasting stock movements by leveraging historical data to project future stock prices (Plastun et al., 2023: 138-146).

The Efficient Market Hypothesis operates under the assumption that financial markets are efficient, indicating that stock prices incorporate all available information. This suggests that, barring any market manipulation, investors cannot consistently exceed market-average returns by analyzing past prices. Numerous studies have been conducted to evaluate the efficiency of various stock markets, and the results have generally supported the validity of the efficient market hypothesis in certain exchanges, including the Kuala Lumpur Stock Exchange (Karakaya, 2024: 134-152). However, the EMH has faced criticism, with some scholars arguing that stock returns possess predictive capabilities that contradict the hypothesis (Cruz-Hernández, 2023: 292-298).

The Efficient Market Hypothesis (EMH) asserts that stock prices follow a random walk and that historical price movements do not serve as reliable predictors of future market behavior (Harabida et al., 2023: 183). Despite this, ongoing discourse and empirical research continue to challenge the foundational assumptions of the EMH (Munir, 2024: 79). In particular, the efficiency of stock markets in developing economies and the MENA region has been subject to scrutiny, with various studies evaluating its weak form efficiency.

Within the context of stock markets, technical analysis employs indicators such as Moving Averages, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD). These are utilized alongside mathematical formulas and graphical representations to identify price patterns that may inform trading decisions (Gurav and Kotrappa, 2020: 6356). Technical analysis seeks to project future price trends through the examination of historical price data and trading volume (Lee et al., 2021: 401-418). While this approach is deemed appropriate for short-term analysis, it is acknowledged that predicting prices over the long term can pose significant challenges (Liu, 2015: 1-93). Conversely, fundamental analysis emphasizes the assessment of a company's intrinsic value via financial statements, performance ratios, and other economic indicators, providing essential information for long-term investors (Afandy et al., 2023: 46-52; Korczak et al., 2016: 1169).

The utilization of technical indicators in stock forecasting has gained considerable traction. Indicators like moving averages, the relative strength index, and Bollinger Bands offer critical insights into stock price dynamics. Investors frequently analyze these metrics to guide their decisions regarding stock purchases and sales (Jain and Vanzara, 2023: 254). Furthermore, advancements in machine learning algorithms have significantly enhanced the accuracy of stock forecasts that leverage these technical indicators. Researchers are increasingly integrating technical indicators with financial performance ratios to improve the precision of stock price projections (Meriç et al., 2017). Financial ratios play an integral role in evaluating a company’s financial health, profitability, and growth potential. Commonly utilized ratios, including Return on Equity (ROE), Return on Assets (ROA), earnings per share, debt-to-equity ratio, and current ratio, measure various aspects of financial performance. These ratios provide valuable insights into operational efficiency, leverage, and liquidity, thereby assisting investors in making well-informed decisions (Lam et al., 2021: 320).

In summary, while the EMH presents a significant theoretical framework for understanding market behavior, the potential efficacy of both technical and fundamental analysis continues to provoke research and debate, particularly in emerging market contexts.

Theoretical Background

Financial Markets

Financial markets represent intricate and dynamic systems that are integral to the functioning of the global economy. They play a vital role in facilitating capital accumulation, risk transfer, and international trade. Comprising various components, including stock markets, bond markets, currency markets, and commodity markets, each segment serves a specific function within the broader financial ecosystem.

The significance of financial markets in driving economic growth has prompted many developing nations to undertake substantial measures aimed at enhancing their financial systems. Nonetheless, despite these initiatives, the growth performance of financial markets often exhibits unevenness across different countries (Emmanuel et al., 2024: 2).

Extensive empirical research has highlighted the critical relationship between financial markets and economic growth. It is posited that well-functioning financial markets are capable of mitigating investment risks while simultaneously bolstering a nation's ability to attract foreign direct investment inflows (Azman-Saini et al., 2010: 211-213).

Functioning as platforms for the trading of financial securities, commodities, and other tradable values, financial markets operate with low transaction costs and reflect prices determined by supply and demand dynamics. They facilitate the transfer of diverse assets—including stocks, bonds, currencies, and derivatives—between buyers and sellers, thereby playing an essential role in the allocation of resources and capital formation within economies (Keister, 2002: 39-61).

Moreover, the relevance of financial markets extends beyond their economic functionalities; they significantly impact individuals, businesses, and governmental entities (Singh, 2017: 1-34). The interplay between financial markets and modern economies remains a salient topic in economic research, particularly concerning the influence of financial development on economic growth and income distribution. Scholars contend that in the nascent stages of economic development, where financial markets are underdeveloped, the pace of economic growth is typically sluggish (Destek et al., 2017: 153-165).

Stock Exchanges

Exchanges play a vital role in enabling the functioning of financial markets. They are legally recognized entities tasked with determining and publishing prices for the trading of stocks, bonds, government securities, and other financial instruments listed on securities exchanges. These transactions help establish the true market values of financial assets. Exchanges can be categorized into two types: public exchanges, which are established by legal authority, and private exchanges, which operate as joint-stock companies governed by private law regulations (Haznedaroğlu, 2009: 1-191).

Serving as centralized marketplaces, exchanges facilitate the buying and selling of various securities, including stocks, bonds, and derivatives, and are integral to the global financial system (Comerton-Forde and Rydge, 2004: 103).

The functions of exchanges are diverse, contributing to the development and regulation of securities trading in capital markets. In their governance activities, exchanges play a crucial role in monitoring, particularly in assisting shareholders with evaluating management performance and implementing effective incentive plans (Hassan, 2017: 20-37).

Stocks

In the realms of finance and trade, stocks represent ownership shares in publicly traded companies, reflecting a proportional interest in the company’s assets and profits. Engaging in stock trading requires dynamic decision-making, including determining the optimal timing, pricing, and quantity of transactions in a highly stochastic and complex market (Liu et al., 2020: 1-12). Stock market manipulation, on the other hand, is an illegal practice that involves artificially inflating or deflating stock prices through covert trading activities (Zulkifley et al., 2023: 4395).

Securities Analysis Methods

Investors and institutions operating within capital markets require a thorough understanding of the market dynamics they engage with, which includes monitoring economic activities, various sectors, and specific organizations. Access to accurate and timely financial information is essential for making informed market forecasts (Morali, 2011: 13-14). Additionally, it is important to take into account the emotions and expectations of individuals. Although making predictions can be challenging, employing a range of analytical methods can significantly enhance the likelihood of success. Furthermore, market professionals—including institutional investors, speculators, manipulators, and other investors who play a role in price determination—can help foster consensus among individuals from diverse cultural, educational, and informational backgrounds, which can be a complex endeavor (Haznedaroğlu, 2009: 11).

Fundamental Analysis

Fundamental analysis is a crucial aspect of financial research that emphasizes the valuation of securities based on accounting irregularities and prevailing market conditions (Richardson et al., 2010: 410). This analytical approach is vital for informing trading decisions; when applied to growth companies, it has been shown to yield abnormal returns (Xue and Zhang, 2011: 306). Additionally, fundamental analysis can be employed to create options-based trading strategies by capitalizing on underlying volatility (Goodman et al., 2013: 1-47). Its application extends beyond stock valuation to portfolio selection, where it plays a significant role in the decision-making process (Zhang and Yan, 2018: 1315). Furthermore, fundamental analysis has been used to assess the value of financial statement information for investors following major market events, such as currency devaluations (Swanson et al., 2003: 875).

The accuracy and transparency of financial reports are fundamental to effective fundamental analysis, and the use of alternative, complementary signals illustrates the wide-ranging applicability of financial statement analysis techniques (Piotroski, 2000: 1).

Technical Analysis

Technical analysis is a widely employed methodology in financial markets that involves the examination of historical market data, particularly price and volume, to forecast future market trends and the behavior of specific stocks (Albeladi and Abdullah, 2018: 68-72). It emphasizes the analysis of market behavior to identify trends and cyclical changes, aiding investors in making informed trading decisions regarding stocks and financial derivatives (Li and Xie, 2022: 326-330).

This analytic approach has been extensively utilized by stock market investors and has remained one of the most popular methods for stock prediction for several decades (Ming and Jais, 2018: 109; Raei et al., 2011: 355). Technical analysis relies on quantitative indicators, such as opening and closing prices and volume, making it particularly effective for short-term stock assessments, although it may face challenges in predicting long-term price movements. Its significance lies in its capacity to educate investors, enabling them to make investment decisions grounded in historical trends of security prices (Masry, 2017: 91). Furthermore, technical analysis incorporates the prediction of stock prices through various technical indicators, including SMA, EMA, RSI, and MACD (Anbalagan and Maheswari, 2015: 214-221).

Efficient Markets Hypothesis

The Efficient Market Hypothesis (EMH) is a foundational theory that elucidates the efficiency of financial markets and the challenges investors face in forecasting market movements. EMH posits that stock prices incorporate all available information, making it difficult for investors to consistently outperform the overall market (Gurung and Sarkar, 2023: 91). Initially proposed by Eugene Fama in 1970, this theory implies that in an efficient market, security prices accurately reflect all relevant information regarding both individual companies and the broader economic landscape. EMH is closely related to the concept of "Random Walk," which suggests that price changes are random and unrelated to past prices (Anelli and Patanè, 2023: 1-10). Consequently, new information is swiftly incorporated into stock prices, complicating efforts for investors to gain an advantage based on existing data (Altahtamouni, 2023: 102).

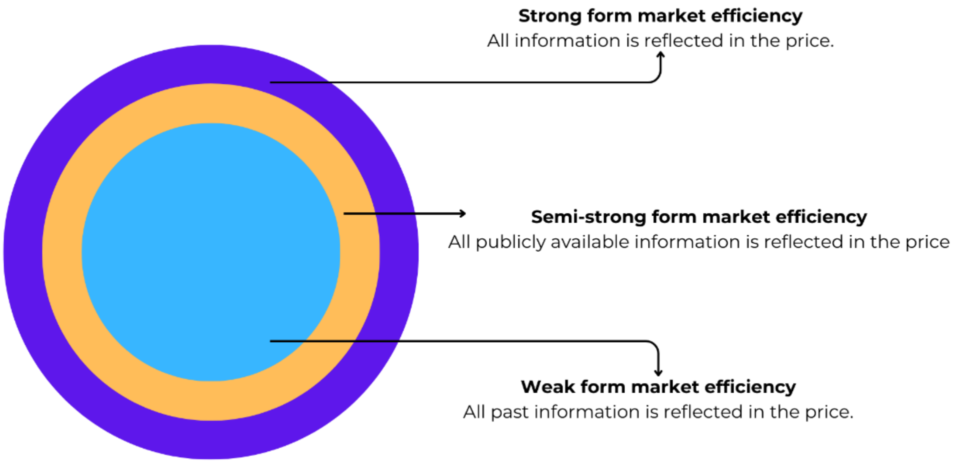
EMH has emerged as a central paradigm in finance and is deeply linked to general equilibrium theory (Gajić, 2023: 172). This hypothesis, which provides valuable insights into market efficiency and the operations of financial markets, has become one of the core tenets of modern economics and finance theory (Ali et al., 2023: 1-5). According to the hypothesis, security prices reflect all presently available information, thereby hindering investors from consistently achieving returns that surpass the market (Enow, 2023: 46). Additionally, it supports the assertion that market efficiency leads to stock prices becoming independent of historical prices (Budiarso and Pontoh, 2023: 24).

The EMH has undergone a variety of tests across different contexts, including emerging markets, while also examining the impacts of market dynamics on various industries (Thalia, 2023: 1816). Furthermore, technological advancements such as machine learning have been employed to explore the predictability of financial markets within the framework of EMH (Zhao, 2023: 1-5).

Forms of Market Efficiency

Fama (1965, 1970, and 1991) conducted a review of empirical studies regarding the random walk of asset prices and proposed various forms of market efficiency under the framework of the Efficient Market Hypothesis (EMH). He categorized market efficiency into three levels: weak form, semi-strong form, and strong form efficiency, based on the types of information reflected in asset prices. According to Fama (1965), each form of EMH suggests that it is unlikely for specific groups of investors to consistently outperform the market by leveraging particular types of information in their trading strategies. As market efficiency increases, the effectiveness of the specific "tools" that investors employ to surpass the market diminishes, as these tools become widely utilized by a majority of investors who adapt their trading behaviors accordingly (Fama, 1970: 388).

Figure 1. Relationships between the three forms of market efficiency



Weak Form Market Efficiency, a concept stemming from the efficient market hypothesis, asserts that all historical market prices and information are fully incorporated into current asset prices. As a result, it is impossible to consistently achieve abnormal returns through the analysis of historical data (Gajić, 2023:171). This form of market efficiency demonstrates, as noted by Kendall and Hill, that stock prices adhere to a random walk model, indicating that future price movements cannot be predicted based on past prices (Yan, 2024: 744-746). In weakly efficient markets, the available information for investors is restricted to previous prices, and any discernible patterns or trends in historical prices are ineffective for forecasting future price movements.

The semi-strong form of market efficiency asserts that all publicly accessible information is instantaneously reflected in asset prices, making it challenging for investors to consistently realize abnormal returns over the long term. This form of efficiency suggests that the rapid integration of public data into stock prices prevents investors from gaining a market advantage through either technical or fundamental analysis. Under the semi-strong form, all public information is absorbed by the market so swiftly that no investor can achieve risk-adjusted returns exceeding normal levels (Fama, 1965: 34-105).

The strong form of efficiency theory posits that no investor, regardless of whether they are utilizing public or private information, can achieve risk-adjusted abnormal returns. This implies that trading based on private or insider information should not consistently yield significant returns, as such outcomes would contradict the principles of strong form efficiency (Agrrawal, 2023: 1-5).

Machine Learning (ML)

The use of machine learning in the financial sector is becoming increasingly prevalent, offering a wide array of applications that enhance financial security, facilitate fraud detection, improve risk management, and optimize decision-making processes.

Artificial Intelligence (AI), a branch of computer science, aims to enhance the intelligence of computers. Learning is a core component of any intelligent behavior, and most researchers today concur that intelligence cannot be achieved without it. As a result, machine learning (ML) stands out as one of the primary branches of AI and is among the fastest-growing areas of AI research (Kononenko, 2001: 89-90).

Machine learning is an ever-evolving area of computational algorithms designed to replicate human intelligence by learning from environmental data. In the era of big data, these algorithms are recognized as the "workhorses" of modern technology. Machine learning techniques have found successful applications across diverse fields, including pattern recognition, computer vision, space exploration, finance, entertainment, computational biology, and medical applications (El Naqa, 2015: 3-11).

The origins of machine learning can be traced back to several disciplines, such as artificial intelligence, neuroscience, cognitive science, and statistics. The concept of intelligent machines was first introduced in 1921 when Čapek coined the term "robot." In 1943, McCulloch and Pitts formulated a rudimentary model of a neuron, which laid the foundation for artificial neural networks. Wiener’s development of the concept of "cybernetics" in 1948, along with Shannon's establishment of the mathematical principles behind communication through information theory during the same period, further advanced the field. In 1956, artificial intelligence was officially recognized as a distinct discipline, and in 1958, Rosenblatt introduced the "perceptron" model. However, due to the perceptron's limitations, Werbos developed the backpropagation algorithm in 1974, which enabled nonlinear learning in multilayer networks. These advancements have facilitated the successful application of neural networks in various tasks, such as classification and regression (Jebara, 2004: 17-60).

Classification is the process of identifying the category to which a new observation belongs, based on a training dataset that contains previously observed categories in machine learning. Examples of classification problems include predicting the winner of a presidential election and categorizing different species of flowers. A binary classification problem involves two classes, while problems with more than two classes are classified as multi-class classification problems. The outcome of a classification task is a discrete value that indicates the class of an observation. Additionally, classification results can also yield a continuous value, representing the probability that an observation belongs to a specific class. For instance, one might predict that candidate A has a 65% chance of winning the election. In this case, 0.65 is the continuous value reflecting the confidence in the prediction, and this can be converted into a discrete class value (winning status) based on the highest probability.

In contrast, regression is a statistical technique used to predict future outcomes by analyzing the relationships between variables. Unlike classification, regression predicts a continuous output variable. Examples of regression problems include sales forecasting, which estimates sales figures for a specific product in the upcoming quarter, and weather forecasting, which uses historical weather data to project temperature changes for the following week.

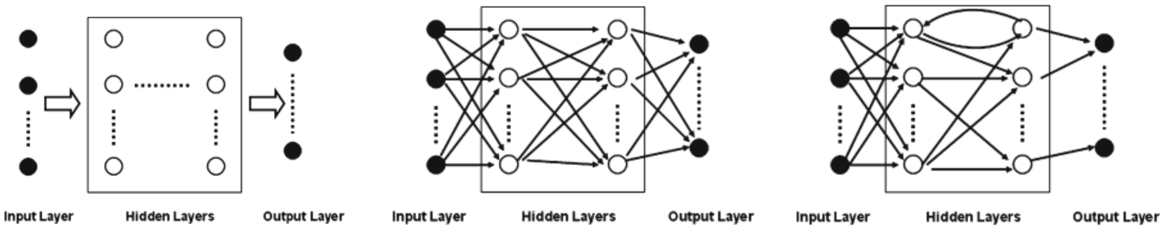
Additionally, regression analysis can be applied to predict the lifespan of products, such as estimating the durability of a particular tire model (Lee, 2019: 4).

Regression analysis is a widely adopted method for understanding the relationships between variables and predicting future values. While the examples provided highlight certain application areas of regression, its utility extends to a vast array of different problems.

Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) are intricate and nonlinear connection systems inspired by the human brain. These networks offer distinct advantages over traditional methods due to their capability to learn relationships between input and output variables (Chhaje et al., 2022). ANNs excel at generalizing from incomplete or noisy data and can produce successful outcomes without requiring prior knowledge of data distribution (Güner et al., 2022). Furthermore, ANNs are effective in identifying patterns within financial markets, enabling the prediction of future price movements. This approach has been employed for forecasting and predictive purposes across various business functions, including finance, accounting, marketing, and production (Raol & Mankame, 1996).

Figure 2. (a) General Topology of ANN, (b) Feed-forward ANN (Sensor), (c) Feedback ANN Structure



- **(a)**
- **(b)**
- **(c)**

Source: (Livingstone, 2008: 20).

Artificial Neural Networks (ANNs) are comprised of three primary layers: the input layer, hidden layer(s), and output layer. The input and output layers correspond to the respective inputs and outputs of the information, with the number of neurons in each layer reflecting the quantity of inputs and outputs. The hidden layer may consist of one or multiple layers, although typically one or two layers are adequate. The number of neurons within the hidden layer influences the network's accuracy and is determined using an empirical formula.

$$h = \sqrt{p + q} + a \tag{1}$$

In this context, “h” represents the number of neurons in the hidden layer, “p” denotes the number of neurons in the input layer, and “q” indicates the number of neurons in the output layer. The constant “a” typically falls within the range of 1 to 10. For addressing nonlinear problems within the hidden layer, log-sigmoid or tan-sigmoid activation functions are utilized. The output layer usually utilizes the purelin function, and the combination of a log-sigmoid hidden layer followed by a purelin output layer tends to yield the highest accuracy.

Log-sigmoid:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

Tan-sigmoid:

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{3}$$

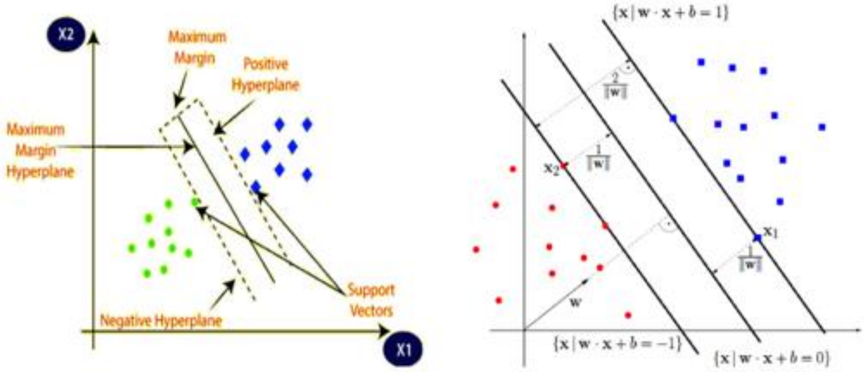
Purelin:

$$f(x) = x \tag{3}$$

Support Vector Machines (SVM)

Support Vector Machines (SVM) represent an advanced approach to machine learning, utilizing classification algorithms specifically designed for binary classification problems. Given labeled training data from distinct categories, SVM has the capability to categorize new texts effectively. Notably, it demonstrates high performance even with a limited amount of data. The primary objective of SVM is to facilitate the classification of linearly separable data. In comparison to Artificial Neural Networks (ANN), SVM is faster and more efficient when dealing with thousands of samples. The goal of SVM models is to establish the optimal hyperplane that separates n-dimensional spaces into distinct groups, allowing new data to be accurately assigned to the appropriate category in the future. The ideal hyperplane is the one that maximizes the margin between the training data points.

Figure 3. SVM hyperplane



Source:(Ahmadi vd., 2018: 22; Chhajer vd., 2022: 6).

The support vector machine is a robust algorithm used for both classification and regression tasks. It employs the principle of structural risk minimization (SRM), allowing for the simultaneous reduction of generalization error. This approach enhances the model's ability to generalize, regardless of the dataset size (Xu et al., 2023: 1).

Table 1. Basic Kernel Functions and Parameters Used in Support Vector Machines

Kernel Functions	**Mathematical Expression**	**Parameter**
Radial Basis Function Kernel	$K(x,y) = e^{-\gamma\|(x-x_i)\|^2}$	Kernel size (γ)
Polynomial Kernel	$K(x,y) = ((x * y) + 1)^d$	Polynomial degree (d)
Normalised Polynomial Kernel	$K(x,y) = \dfrac{((x,y) + 1)^d}{\sqrt{((x * x) + 1)^d((y * y) + 1)^d}}$	Polynomial degree (d)

Pearson VII (PUK) Kerneli	$\frac{1}{\left[1+\left(\frac{2*\sqrt{\lVert x-y\rVert^{2}\sqrt{2^{(1/\omega)}-1}}}{\sigma}\right)^{2}\right]^{\omega}}$	Pearson width parameters (σ , ω)

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based optimization technique introduced by J. Kennedy and R.C. Eberhart in 1995, drawing inspiration from the behaviors of bird flocks. It effectively addresses multi-variable and multi-parameter non-linear problems. The PSO algorithm initiates with randomly generated solutions, akin to genetic algorithms, and continuously refines these solutions in search of the optimal one. However, unlike genetic algorithms, PSO does not incorporate crossover and mutation operations, simplifying its application. In PSO, potential solutions, referred to as particles, possess position and velocity vectors. These particles navigate the solution space by leveraging information from the particle that has identified the best solution over time (Eltawil and Zhao, 2013: 110-120).

The process of PSO begins with a randomly initialized swarm of particles, each likened to a "bird" within the search space. Each particle maintains its best position and updates its location at each iteration to approach the global optimum. These updates take into account pbest, which indicates the best position achieved by each individual particle, and gbest, representing the most successful position attained by the entire swarm. A particle population matrix facilitates these operations (Salman and Aksoy, 2022: 416-423).

Literature Review

Stock Prediction Studies with ML

The predictive modeling of stock market indices has garnered significant research attention in the field of financial analytics. Wang et al. (2012) introduced a hybrid model known as the Predictive Hybrid Model (PHM), which integrates Exponential Smoothing Model (ESM), Autoregressive Integrated Moving Average (ARIMA), and Back Propagation Neural Network (BPNN) approaches to ascertain the direction of stock index movements. The weights attributed to the varied components of PHM were optimized via Genetic Algorithm (GA). A comparative analysis was conducted against several benchmarks, including the ESM, ARIMA, BPNN, an Equal Weighted Hybrid Model (EWM), and a Random Walk Model (RWM), employing monthly opening data from the Shenzhen Composite Index (SZII) and the Dow Jones Industrial Average (DJIA). Prediction performance was rigorously assessed using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Error (ME), and Direction Accuracy (DA). The results indicated that the hybrid model attained a prediction accuracy of 70.16% for both SZII and DJIA, outperforming all traditional forecasting models.

Kaur and Mangat (2013) sought to refine the accuracy of the Support Vector Machine (SVM) model for stock price forecasting by employing Particle Swarm Optimization (PSO) and Differential Evolution (DE) methods. Their dataset comprised daily stock prices from major corporations, including Honeywell International Inc. and Apple Inc., with inputs that encompassed opening price, high, low, adjusted closing price, and trading volume; the output reflected the subsequent day's closing price. Mean Squared Error (MSE) served as the evaluation criterion for model performance. The study juxtaposed the performance of hybrid models DE-SVM and PSO-SVM against the standard SVM model, revealing that both hybrid approaches substantially enhanced predictions during training and testing phases. These findings underscored that optimized parameter configurations critically bolster SVM's predictive capability.

Chandwani (2014) undertook an investigation of market indicators via machine learning techniques in the Indian stock market. This study employed three distinct approaches—fundamental modeling, technical indicators modeling, and a hybrid model—utilizing independent machine learning algorithms such as SVM, Artificial Neural Network (ANN), GA-SVM, and GA-ANN. The goal was to ascertain which methodology most accurately forecasted stock price movements in India. The results affirmed that the incorporation of GA significantly improved ANN accuracy, and highlighted the efficacy of SVM and ANN, particularly in conjunction with technical analysis, for Indian equities. Such insights hold substantial promise for enhancing trading strategies and investment profitability.

In a similar vein, Sidduque et al. (2017) developed a hybrid model leveraging Particle Swarm Optimization and Artificial Neural Networks (PSO-ANN) to predict stock prices. This model demonstrated exceptional accuracy with a low Mean Absolute Percentage Error (MAPE) of 1%, effectively predicting the daily high values of stock prices and surpassing the performance of existing models.

Moreover, Dito et al. (2020) conducted a case study utilizing Support Vector Machine (SVM) for stock trend forecasting. The study achieved a prediction accuracy of approximately 65% for one-day-ahead predictions, further emphasizing SVM's potential as a robust tool in stock price prediction landscapes.

These studies collectively underscore the growing significance of hybrid models and advanced optimization techniques in enhancing the accuracy and efficacy of stock market predictions**.**

Prediction Studies Using Financial Ratios

Liang et al. (2016) conducted an exploration into bankruptcy prediction by merging financial ratios with corporate governance indicators, resulting in the proposal of a comprehensive framework for forecasting financial outcomes. Their findings indicate that the integration of financial ratios alongside corporate governance metrics substantially enhances model performance in the context of bankruptcy prediction.

Öztürk and Karabulut (2017) investigated the relationship between financial ratios and stock returns for companies within the technology and communication sectors listed on the Istanbul Stock Exchange (İMKB). The study aimed to elucidate the influence of financial ratios on stock returns through the lens of weak form market efficiency theory. Utilizing quarterly data encompassing 14 companies from 2008 to 2016, they conducted a panel data analysis focusing on the earnings/price ratio (E/P), current ratio, and net profit margin as independent variables. Employing a two-way fixed effects model alongside the Parks-Kmenta and Beck-Katz methodologies, the study revealed that both the E/P ratio and net profit margin exhibit significant effects on stock returns, whereas the current ratio did not demonstrate a statistically significant impact. Consequently, the research concluded that stocks characterized by elevated E/P ratios and profit margins yield higher returns in subsequent periods.

Özkan (2018) investigated the weak form efficiency of Borsa İstanbul (BIST) using data spanning from July 2009 to June 2016. The analysis involved the development of the Fama-French three-factor model, the Carhart four-factor model, and the q-factor model to assess their explanatory power concerning stock returns. The results established that the BIST 100 index is weak form efficient, indicating that historical price information is effectively reflected in current prices and suggesting that technical analysis methods yield no potential gains. Notably, the investigation revealed that the q-factor model exhibits superior explanatory power relative to both the Fama-French and Carhart models. Ultimately, the findings affirm the weak form efficiency of the BIST 100 and highlight the q-factor model as possessing the most robust explanatory capability.

Çelik and Arslan (2021) engaged in predicting the financial failures of firms listed on the BIST 100 index using logistic regression analysis. Their investigation encompassed an examination of various financial ratios, including the interest coverage ratio, operating profit margin, current ratio, accounts receivable turnover, asset turnover, and equity turnover for 26 firms in 2019. The researchers developed three distinct logistic regression models, achieving a highest correct prediction rate of 92.31%. The analysis identified the interest coverage ratio and operating profit margin as critical determinants in differentiating between successful and unsuccessful firms. This study contributes significantly to the discourse on predicting financial failures, establishing itself as a valuable forecasting and monitoring tool for business proprietors and investors.

Methodology

In developing a model for stock price prediction, the most commonly referenced variables in both fundamental and technical analysis from existing literature have been employed. The dependent variable in the regression models is identified as the Stock Closing Price, while the independent variables include the Stock Opening Price, Stock Low Price, Stock High Price, Weighted Average, Trading Volume, Trading Quantity, Bollinger Bands, Moving Average, Commodity Channel Index (CCI), Moving Average Convergence Divergence (MACD), Momentum, Relative Strength Index (RSI), Stochastic Oscillator, Williams %R, Earnings Per Share Ratio, Price-to-Earnings Ratio, Net Profit Margin, Return on Equity Ratio, Debt-to-Equity Ratio, Return on Assets Ratio, Total Assets, Asset Growth, Leverage Ratio, Net Working Capital Turnover Ratio, Market Value-to-Book Value Ratio, Current Ratio, Acid-Test Ratio, Cash Ratio, Current Assets-to-Total Assets Ratio, Equity-to-Total Assets Ratio, and Market Value-to-Total Assets Ratio. These financial ratios and indicators are employed to assess a company's financial condition and performance. Data for these variables, spanning from 1993 to 2023, has been collected in dollar terms on an annual basis, divided into four quarters, by Finnet Electronic Publishing Data Communication Industry Trade Ltd. Co. To identify the model that most accurately predicts the Stock Closing Price, four distinct models have been developed for each stock using the Python programming language.

Data Collection

This study presents an analysis of four companies that have demonstrated consistent performance within the BIST 100 index in Turkey over a thirty-year period, from 1993 to 2023. The following table categorizes these companies according to their respective sectors.

Table 2. Stocks used in the research

Sector	Share No	Abbreviation	Share Name
Financial Institutions / Holdings and Investment Companies	1	ALARK	Alarko Holding Inc.
	2	DOHOL	Doğan Companies Group Holding Inc.
	3	ECILC	Eczacıbaşı Pharmaceutical Industrial and Financial Investments Industry and Trade Inc.
	4	SISE	Turkey Glass and Glassware Factories Inc.

In conducting the analysis for this study, a comprehensive selection of variables was employed, comprising seven fundamental stock market data points, eleven technical indicators, and seventeen metrics derived from financial performance ratios. These variables are systematically outlined in the accompanying table and have been sourced from Finnet Elektronik Yayıncılık Data İletişim San. Tic. Ltd. Şti. This meticulous selection aims to ensure a robust framework for the analysis, facilitating a nuanced understanding of the relationships among the variables studied.

Table 3. Variables used in the application

Abbreviation	Variables	Group	Literature
A	Stock Trading Quantity	Fundamental Data	Kumar et al., (2021);Kara et al., (2011);Wang et al., (2021);Huang et al., (2021)
K	Bollinger Band Upper Band	Fundamental Data	Kumar et al., (2021);Kara et al., (2011);Wang et al., (2021);Huang et al., (2021)
D	Bollinger Band Lower Band	Fundamental Data	Kumar et al., (2021);Kara et al., (2011);Wang et al., (2021);Huang et al., (2021)
Y	Commodity Channel Index (CCI)	Fundamental Data	Kumar et al., (2021);Kara et al., (2011);Wang et al., 2021);Huang et al., (2021)
AO	Moving Averages	Fundamental Data	Alaca and Aysun, (2022);Jeong et al., (2021);Chen vd., (2020);Safi and Dawoud, (2013)
İH	MACD	Fundamental Data	Huang et al., (2021);Qiu et al., (2020);Lu et al., (2021);Tekin and Canakoglu, (2019)
İM	MACD (Moving Average Convergence Divergence)	Fundamental Data	Huang et al., (2021);Chen et al., (2020)

BB	Momentum	Technical Indicator	Khairi et al., (2019);Kannan et al., (2010);Teixeira and Oliveira, (2009);Vargas et al., (2018)
BB	Relative Strength Index (RSI)	Technical Indicator	Khairi et al., (2019);Kannan et al., 2010);Teixeira and Oliveira, (2009);Vargas et al., (2018)
CCI	Stochastic Oscillator	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Prachyachuwong and Vateekul, (2021);
HO	Stochastic Oscillator Moving Average	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Alaca and Aysun, (2022);Prachyachuwong and Vateekul, (2021)
MACD	Larry Williams %R	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Prachyachuwong and Vateekul, (2021);Khairi et al., (2019)
MACD-HO	Current Ratio	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Prachyachuwong and Vateekul, (2021);Khairi et al., (2019)
MOM	Acid-Test Ratio	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Vargas et al., (2018)
RSI	Cash Ratio	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Prachyachuwong and Vateekul, (2021);Khairi et al., (2019)
STO	Leverage Ratio	Technical Indicator	Kumar et al., (2021);Kara et al., (2011);Alaca and

			Aysun, (2022);Khairi et al., (2019)
STO-HO	Earnings Per Share (EPS)	Technical Indicator	Kumar et al., (2021);Kara vd., (2011);Alaca and Aysun, (2022);Khairi et al., (2019)
W%R	Price-to-Earnings Ratio (P/E)	Technical Indicator	Kara et al., (2011);Prachyachuwong and Vateekul, (2021);Agrawal et al., (2022);Vargas et al., (2018)
CO	Net Profit Margin	Financial Performance	Tsai et al., (2023);Milosevic, (2016);Şeyranlioğlu and Karavardar, (2024); Ballings et al., (2015)
ATO	Return on Equity (ROE)	Financial Performance	Milosevic, (2016); Şeyranlioğlu and Karavardar, (2024);Ballings et al., (2015)
NO	Return on Assets (ROA)	Financial Performance	Şeyranlioğlu and Karavardar, (2024); Ballings et al., (2015);Gümüş et al., (2017)
KO	Debt-to-Equity Ratio (D/E)	Financial Performance	Ballings et al., (2015); Şeyranlioğlu and Karavardar, (2024);Gümüş et al., (2017)
HKO	Assets	Financial Performance	Şeyranlioğlu and Karavardar, (2024);Karagül, (2014); Huang et al., (2021);Chen et al., (2017)
FKO	Asset Growth	Financial Performance	Şeyranlioğlu and Karavardar, (2024); Ballings et al.,

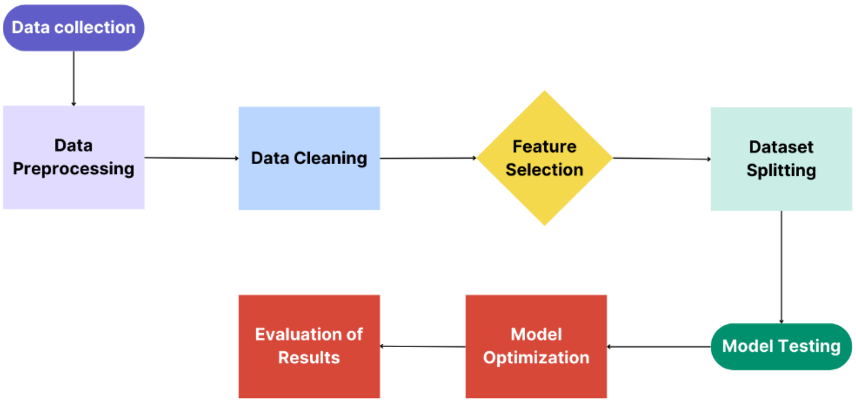
			(2015);Karagül, (2014);Huang, (2012)
NKO	Net Working Capital Turnover Ratio	Financial Performance	Tsai et al., (2023); Milosevic, (2016); Şeyranlioğlu and Karavardar, (2024);Huang et al., (2021)
ÖKO	Market Value / Book Value Ratio	Financial Performance	Tsai et al., (2023); Şeyranlioğlu and Karavardar, (2024); Ballings et al., (2015);Wilimowska and Krzysztoszek, (2013)
AKO	Current Assets / Total Assets	Financial Performance	Tsai et al., (2023); Şeyranlioğlu and Karavardar, (2024); Ballings et al., (2015);Huang et al., (2021)
B/ÖO	Equity / Total Assets	Financial Performance	Tsai et al., (2023);Tuna and Karaca, (2015);Bonello et al., (2018);Yang et al., (2018)
AK	Stock Trading Quantity	Financial Performance	Şeyranlioğlu and Karavardar, (2024);Lombardo et al., (2022);Ustalı et al., (2021)
AB	Bollinger Band Upper Band	Financial Performance	Hájek et al., (2013);Cooper et al., (2008);Dou et al., (2012);Ceyhan, (2023)
NÇO	Bollinger Band Lower Band	Financial Performance	Tsai et al., (2023);Karagül, (2014); Fatih Ateş, (2023);Ceyhan, (2023)
PD/DD	Commodity Channel Index (CCI)	Financial Performance	Milosevic, (2016); Şeyranlioğlu and Karavardar, (2024); Karagül, (2014); Huang et al., (2021)

DV/A	Moving Averages	Financial Performance	Ceyhan, (2023);Emir et al., (2012)
Ö/A	MACD	Financial Performance	Şeyranlioğlu and Karavardar, (2024);Fatih Ateş, (2023);Ustalı et al., (2021);Emir et al., (2012)
PD/A	MACD (Moving Average Convergence Divergence)	Financial Performance	Omar et al., (2022);(Gu et al., 2020);Ceyhan, (2023)

To develop models for predicting the prices of stocks traded on the BIST 100, a comprehensive literature review was conducted, leading to the selection of 35 relevant variables. Various machine learning techniques, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Particle Swarm Optimization (PSO) models, were employed, along with the creation of hybrid models. During the model development process, Python libraries such as Numpy, Matplotlib, Pandas, Scikit-learn, Seaborn, TensorFlow, and Keras were utilized.

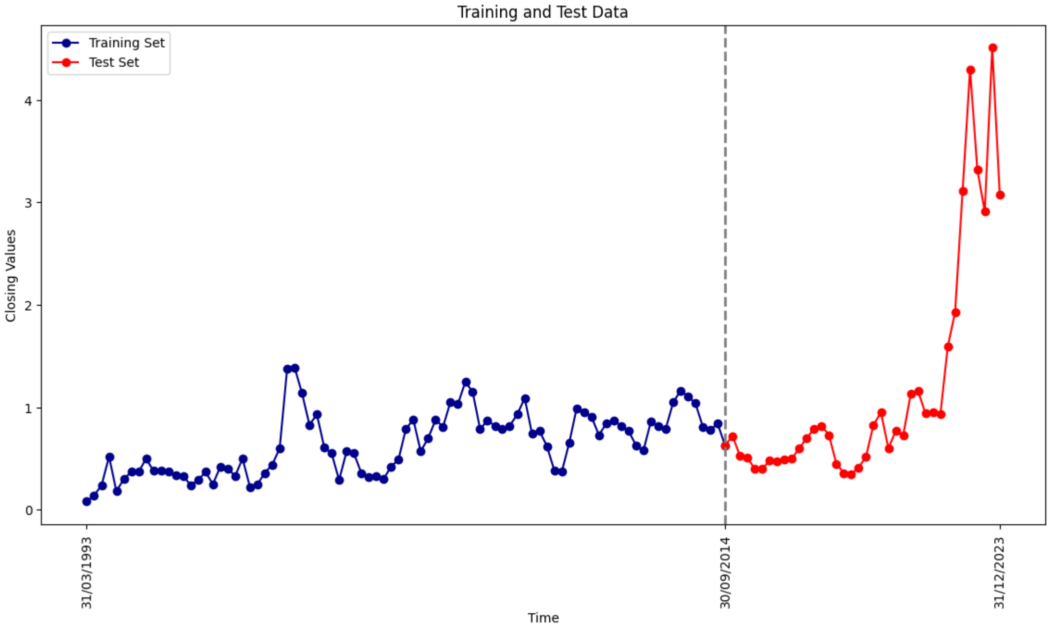
The primary objective of this study is to create forecasting models for stocks that have been continuously traded on the Borsa İstanbul National 100 Index (BIST 100) from 1993 to 2023. This research aims to compare the performance metrics of four distinct models, employing both fundamental and technical analysis in conjunction with hybrid models to predict stock prices. In this context, the study addresses several key research questions.

Figure 4. Workflow



The process of dividing the dataset into training and test sets involves separating the data into distinct subsets for the purposes of model training and evaluation. This division can be executed using various ratios such as 10:90, 20:80, 30:70, 40:60, 50:50, 60:40, 70:30, 80:20, and 90:10. In this configuration, the training dataset is utilized to build the model, whereas the test dataset is employed to assess the model's predictive capabilities (Nguyen et al., 2021: 15). Fig. 5 illustrates a graph depicting how the training and test data for ALARK company were allocated.

Figure 5. Dataset splitting



In our model comparisons, we prefer to utilize multiple metrics rather than relying on a single performance criterion. The metrics selected are widely recognized and examined in the literature. These include Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and R². Together, these metrics provide a well-rounded assessment of model performance, illuminating both the strengths and weaknesses of each approach. Consequently, employing these performance metrics enhances the accuracy and reliability of our models, ensuring that our findings are valid and broadly accepted.

Within the realm of stock price prediction using machine learning, several essential metrics and techniques significantly contribute to evaluating and enhancing the predictive performance of models. Utilizing metrics like R², Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) is critical for assessing the accuracy and dependability of stock price forecasts. R², often referred to as the coefficient of determination, offers insight into the proportion of variance in the dependent variable (stock price) that can be attributed to the independent variables utilized in the model (Huang, 2023: 26-28). A high R² value signifies that the model accounts for a substantial portion of the variability in stock prices, rendering it a valuable metric for evaluating prediction accuracy.

Results

Prediction with ANN

In the study, the artificial neural network (ANN) model developed for predicting stock closing prices is organized based on the parameters outlined in Table 4. This model features a three-layer architecture, with each layer serving distinct functions. The first two layers each contain 128 units and utilize the ReLU activation function. To mitigate the risk of overfitting, a dropout rate of 20% is implemented between these layers. The final layer consists of a single unit and does not incorporate an activation function.

Table 4. ANN model parameters

Layer	Units	Activation	Dropout
Dense	128	ReLU	0.2
Dense	128	ReLU	0.2
Dense	1	-	-
Other Parameters	**Value**		
Optimisation Method	Adam		
Loss Function	Mean Squared Error (MSE)		
Epoch	1000		
Batch Size	32		

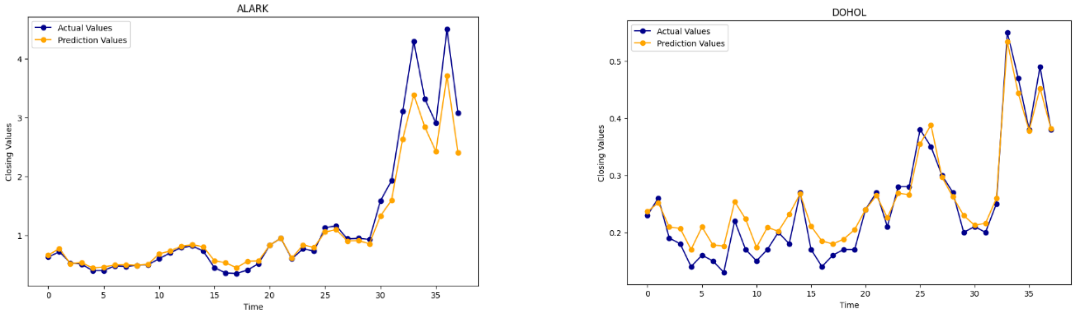
The model underwent training for a total of 1,000 epochs, utilizing a batch size of 32 data samples for each training cycle. These parameters were meticulously chosen and optimized to improve the model's performance and predictive accuracy. In the study, the model's performance was assessed using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE).

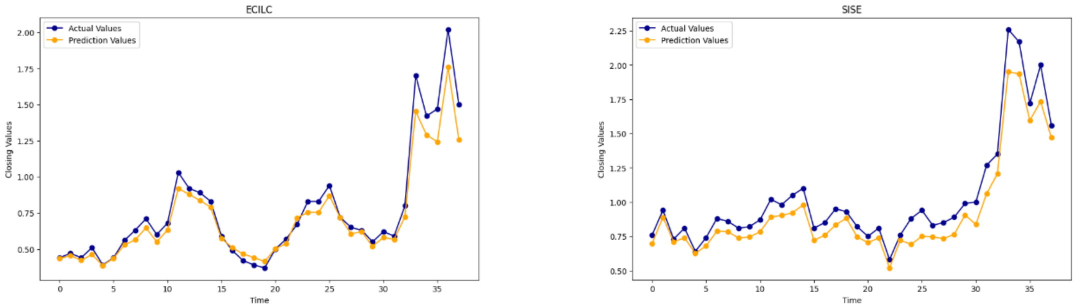
Table 5. ANN model performance results

Companies	MSE	MAE	R^2	MAPE
ALARK	0.1027	0.1801	0.9152	13.4959
DOHOL	0.0012	0.0274	0.8826	13.8739
ECILC	0.0144	0.0745	0.9012	7.8232
SISE	0.021	0.1072	0.8661	9.2506

According to the results presented in Table 5, the predictive model for ALARK Company demonstrates strong accuracy with a high R^2 value of 0.9152. However, the MAPE value of 13.4959% indicates a relatively higher margin of error. On the other hand, DOHOL has exhibited exceptional performance with the lowest MSE of 0.0012 and MAE of 0.0274. Nevertheless, its R^2 value of 0.8826 and MAPE of 13.8739% are not as robust as those of ALARK and ECILC. ECILC stands out with the best results in the table, showcasing low MSE at 0.0144 and MAE at 0.0745, alongside a high R^2 of 0.9012 and the lowest MAPE of 7.8232%. The performance of SISE Company is satisfactory, with medium-level MSE of 0.021 and MAE of 0.1072. Although its R^2 value of 0.8661 is lower compared to other companies, it still signifies an acceptable level of accuracy. Furthermore, the MAPE value of 9.2506% indicates a reasonable error rate. In summary, ECILC is the standout company in the table, while ALARK and DOHOL could benefit from improvements in their MAPE values for enhanced results.

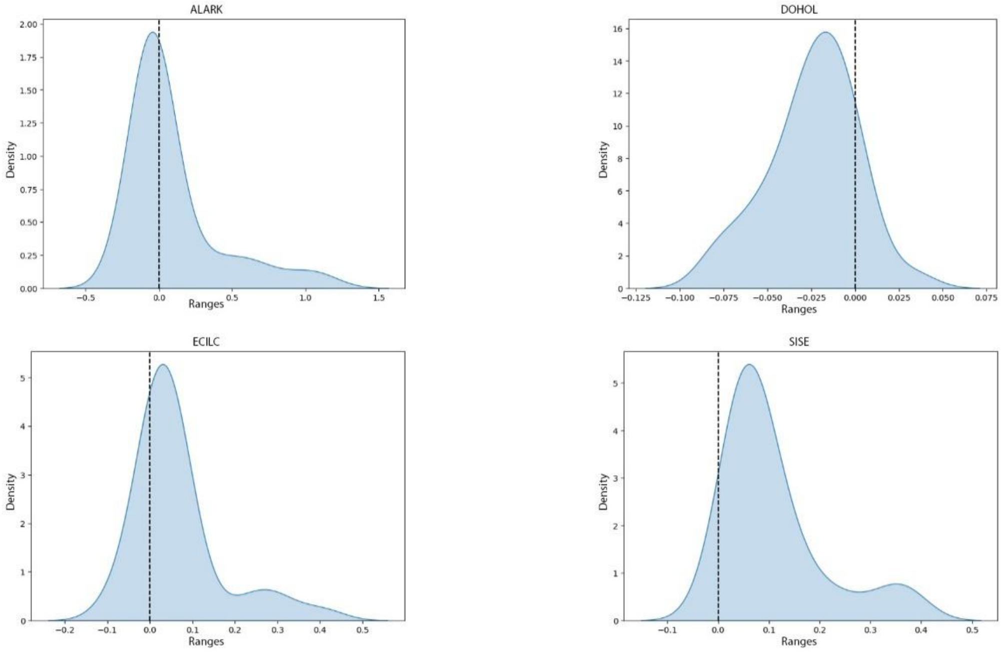
Figure 6. Performance graph of ANN model with actual and predicted values





In Fig. 6, it is evident that the ANN model consistently demonstrates a high level of concordance between actual and predicted values. Notably, the model excels in tracking fluctuations in the ALARK and ECILC parameters. Although a parallelism in general trends has been established for the DOHOL and SISE parameters, minor discrepancies have been observed in certain outlier values. While the model is largely proficient in capturing sudden changes, further optimizations could enhance its performance at these extreme points. Overall, the ANN showcases strong predictive capabilities for parameters characterized by fluctuating data structures.

Figure 7. Density plot of companies with ANN model



In Fig. 7, the distribution of prediction errors from the ANN model has been analyzed, revealing that the errors tend to cluster around the central tendency for each parameter (ALARK, DOHOL, ECILC, SISE). The density curves for all parameters exhibit a relatively symmetric shape, which indicates that the model's prediction errors predominantly remain at low levels. This finding suggests that the ANN model generally operates with low deviation in its predictions, thereby yielding reliable results. Nevertheless, the presence of some outliers in the graphs highlights potential areas for improvement, particularly in enhancing the model's performance in extreme scenarios.

Prediction with SVM

In this study, various machine learning models were employed to predict stock closing prices, including the Support Vector Machine (SVM) model. The parameters of the SVM model play a crucial role in influencing its performance. The parameter values utilized in this study are presented in Table 6. The "C" parameter acts as a regularization parameter that balances the model's error tolerance with its accuracy; in this case, it has been set to 1000. The "Epsilon" parameter gauges the model's sensitivity and has been selected at 0.001. Additionally, the "Gamma" parameter, which defines the range of influence for the RBF kernel function, has also been set to 0.001. The kernel function chosen for this model is the Radial Basis Function (RBF). These parameter selections were made with careful consideration to optimize the model's performance.

Table 6. SVM model parameters

Parameter	**Value**
C	1000
epsilon	0,001
gamma	0,001
kernel	rbf

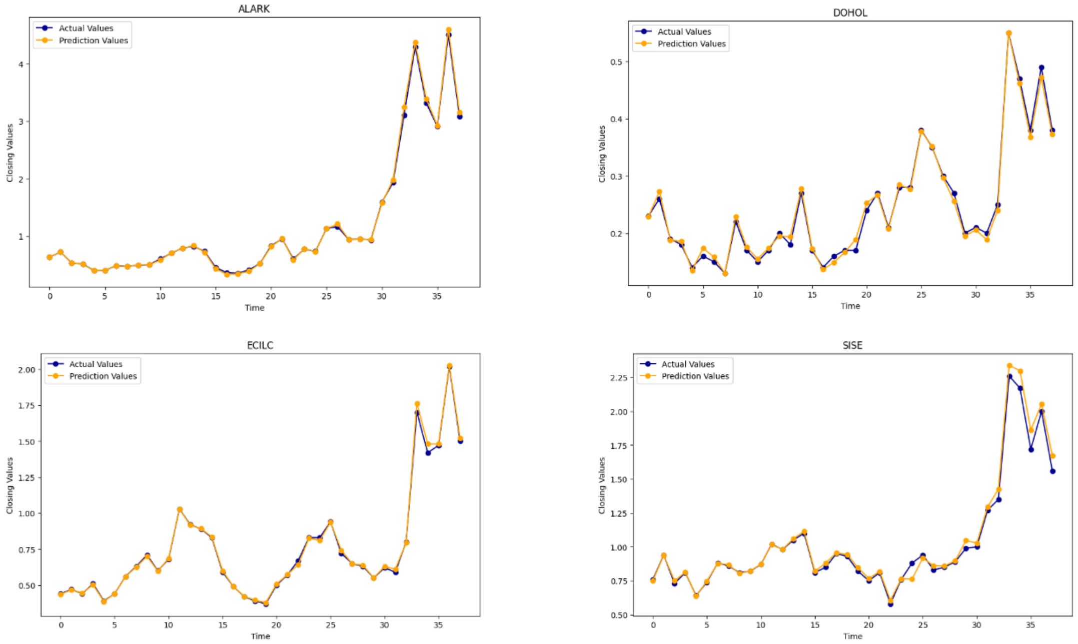
The parameters of the SVM model presented in Table 6 have been finely tuned to ensure a high level of accuracy. A value of C=1000 reflects a strategic balance aimed at minimizing errors, while an epsilon value of 0.001 effectively restricts prediction deviations in the regression model. The relatively low gamma value of 0.001 enhances the flexibility of the decision boundaries, and the use of the RBF kernel has proven successful in capturing nonlinear relationships within complex datasets. These carefully chosen parameters have significantly contributed to the model's robust performance, particularly in balanced datasets.

Table 7. SVM model performance results

Companies	**MSE**	**MAE**	**R^2**	**MAPE**
ALARK	0,0014	0,0210	0,9989	1,6686
DOHOL	0,0001	0,0069	0,9931	3,1600
ECILC	0,0003	0,0099	0,9980	1,1922
SISE	0,0023	0,0295	0,9853	2,4797

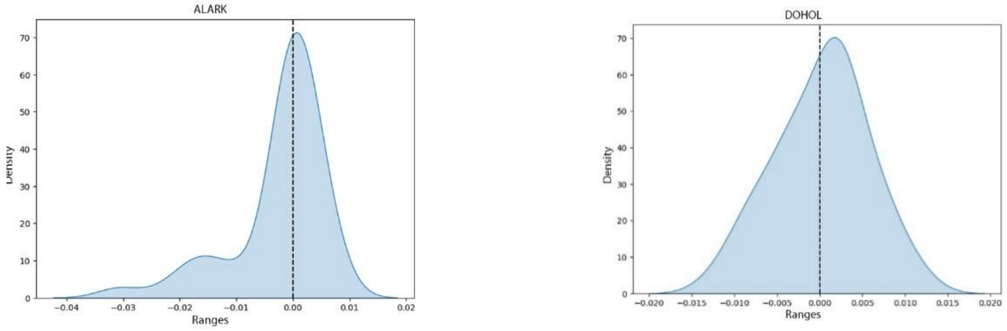
The findings presented in Table 7 indicate that the predictive model for ALARK company exhibits strong accuracy, achieving a high R^2 value of 0.9989. Additionally, the MAPE value of 1.6686% reflects a relatively low percentage error in its predictions. DOHOL stands out with the lowest Mean Squared Error (MSE) of 0.0001 and Mean Absolute Error (MAE) of 0.0069. Although it maintains a high R^2 value of 0.9931, its MAPE of 3.1600% is comparatively higher than that of other companies. ECILC demonstrates the most impressive results in the table, characterized by a low MSE of 0.0003, an MAE of 0.0099, a high R^2 value of 0.9980, and the lowest MAPE at 1.1922%. SISE shows satisfactory performance, with moderate MSE of 0.0023 and an MAE of 0.0295. Though its R^2 value of 0.9853 is lower than those of its competitors, it still offers an adequate level of accuracy. Furthermore, the MAPE of 2.4797% indicates that the error rate is acceptable. In summary, the ECILC company achieves the best overall results, whereas there remains an opportunity for improvement in DOHOL’s model performance by lowering its percentage error.

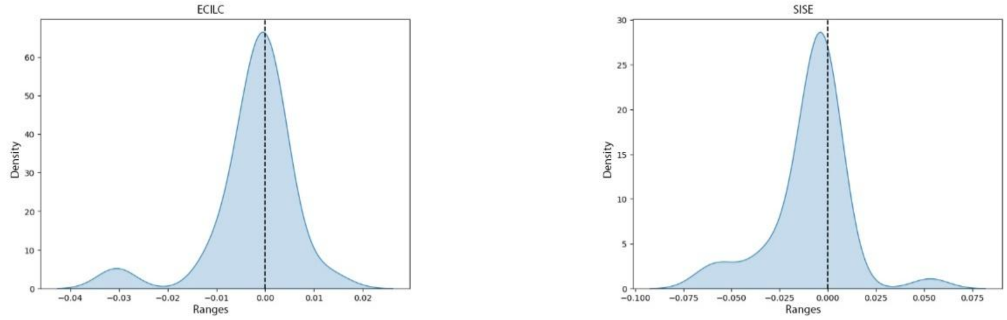
Figure 8. Performance graph of SVM model with actual and predicted values



The graphs presented in Fig. 8 illustrate the performance of the SVM model in relation to the actual and predicted values. It is evident that the predicted values for all companies closely align with the actual values, suggesting that the model achieves a commendable level of accuracy overall. For ALARK and ECILC, the model has exhibited stable performance, particularly in capturing actual values during periods of sudden increases and decreases. In the case of DOHOL, the model's predictions align well with the fluctuating data structure, although slight deviations are present in some outliers. Regarding SISE, the predictions accurately reflect the general trends, though minor differences can be noted at certain peaks. These findings indicate that the SVM model can attain high accuracy rates, even when dealing with complex data structures; however, enhancing its ability to handle outliers could potentially yield even more effective results. Overall, the graphs substantiate the robust predictive power of the SVM model, demonstrating its reliability as a tool for performance forecasting across various companies.

Figure 9. Density plot of companies with SVM model





In the density graphs presented in Fig. 9, the distribution of prediction errors from the SVM model has been analyzed. It is noted that the errors cluster around the central tendency for each company. For ALARK and ECILC, the concentration of errors within a very narrow range signifies a high level of prediction accuracy achieved by the model. In the case of DOHOL, while the prediction errors also fall within a low-density range, a slight asymmetry compared to the other companies is noteworthy. The density curve for SISE, on the other hand, appears symmetrical, with errors primarily concentrated in a central region. These graphs illustrate that the SVM model generally operates with low error rates and demonstrates consistent performance in its predictions. Nonetheless, the minor asymmetry in the density distribution for DOHOL suggests that there may be room for slight improvement in the model's application to this company's data. Overall, the graphs reinforce the idea that the SVM model is a reliable tool for predictions.

Prediction with PSO-ANN

In this study, various parameters were optimized using Particle Swarm Optimization (PSO) to improve the performance of the PSO-Artificial Neural Network (ANN) model. The parameter values for the PSO-ANN model employed in this research are detailed in Table 8. The optimization process encompassed the number of units in the Dense layer, the choice of activation function, and the input shape, all determined through PSO. The output layer consisted of a single unit. The Adam optimization algorithm was utilized, with the learning rate also optimized through PSO. Mean squared error served as the loss function, and the model underwent training for 1000 epochs. Additionally, the batch size parameter was optimized via PSO. For the configuration of PSO, a swarm size of 10 was established, and the maximum number of iterations was set to 20.

Table 8. PSO-ANN hybrid model parameters

Parameter	**Value**
Dense Layer	units=PSO optimised with, activation='relu', input_shape=(X_train.shape[1],)
Dense (Output layer)	units=1
optimizer	Adam
learning_rate	Optimized with PSO
loss	mean_squared_error
epochs	1000
batch_size	Optimized with PSO
PSO Swarm Size	10
PSO Max Iteration	20

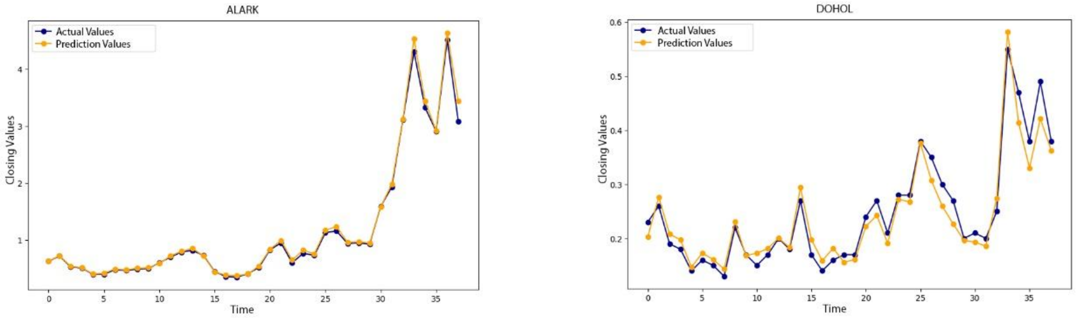
The parameters of the PSO-ANN model, as outlined in Table 8, were optimized using the Particle Swarm Optimization (PSO) algorithm to enhance overall model performance. Key hyperparameters, including the number of units in the dense layer, learning rate, and batch size, were fine-tuned through PSO. The Adam optimizer in conjunction with the mean squared error loss function was utilized to minimize the model's error rate. With the training extended over 1000 epochs, long-term learning was achieved. Furthermore, the use of a swarm consisting of 10 particles over 20 iterations showcases the optimization capabilities of PSO. This configuration has significantly contributed to the model's proficiency in learning from complex datasets.

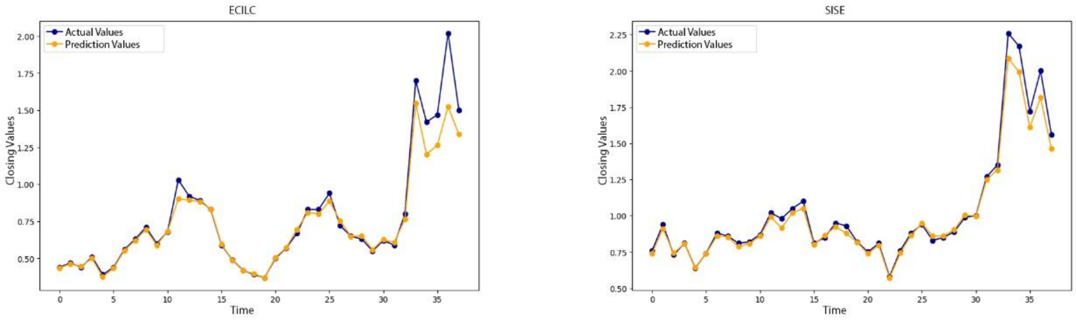
Table 9. PSO-ANN hybrid model performance results

Companies	MSE	MAE	R^2	MAPE
ALARK	0,0060	0,0403	0,9950	3,2285
DOHOL	0,0007	0,0206	0,9366	8,3040
ECILC	0,0109	0,0467	0,9255	3,8866
SISE	0,0036	0,0357	0,9773	2,7426

In Table 9, the performance metrics of the Particle Swarm Optimization coupled with Artificial Neural Networks (PSO-ANN) model are meticulously analyzed. The results for ALARK indicate a robust predictive accuracy, characterized by a high coefficient of determination (R^2) value of 0.9950 and a minimal mean squared error (MSE) of 0.0060. Furthermore, the mean absolute percentage error (MAPE) of 3.2285% suggests an acceptable margin of error within the predictions. DOHOL exhibits noteworthy performance, presenting the lowest MSE at 0.0007 and a mean absolute error (MAE) of 0.0206, alongside a competent R^2 value of 0.9366; however, its MAPE of 8.3040% is comparatively elevated. ECILC demonstrates satisfactory predictive accuracy with an R^2 of 0.9255 and an MSE of 0.0109, although its MAPE of 3.8866% is slightly higher than that observed for ALARK and SISE. SISE stands out as the most effective performer, showcasing a low MSE of 0.0036, an MAE of 0.0357, and a high R^2 value of 0.9773, in addition to possessing the lowest MAPE at 2.7426%. Collectively, while SISE demonstrates the best overall performance, enhancing the MAPE value for DOHOL could further strengthen the model’s predictive capabilities. These findings affirm that the PSO-ANN model serves as a generally reliable and effective forecasting instrument.

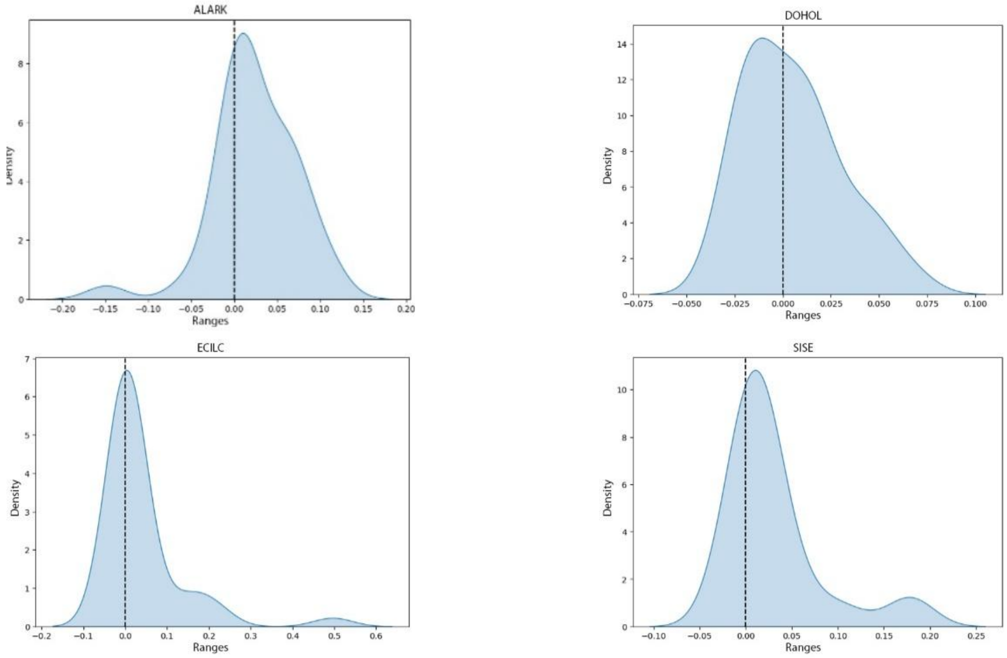
Figure 10. Performance graph of PSO-ANN hybrid model with actual and predicted values





In Fig. 10, the performance of the PSO-ANN hybrid model is illustrated through a comparison of actual and predicted values. For ALARK, the model demonstrates a significant overlap between predicted and actual values, particularly showcasing high accuracy during sudden fluctuations. At DOHOL, although the model effectively tracks the variable data patterns, it does exhibit minor deviations at certain outliers. For ECILC, the predicted values generally align well with the actual values in terms of trends and fluctuations, though some discrepancies are noted at specific points. At SISE, the predictions maintain strong alignment with overall trends and closely match the actual values. Overall, the graphs suggest that the PSO-ANN model performs robustly across all companies, particularly yielding consistent results for ALARK and SISE. However, addressing the performance on outliers for DOHOL and ECILC could further enhance the model's accuracy.

Figure 11. Density plot of companies with PSO-ANN hybrid model



In Fig. 11, the density distributions of the prediction errors from the PSO-ANN hybrid model are analyzed. It is noted that the density of prediction errors is concentrated within a narrow range and exhibits symmetry for the ALARK and SISE companies, suggesting that the model maintains consistent and low error rates in its predictions. In contrast, for DOHOL, the prediction errors exhibit slight asymmetry, with the density spreading across a broader range; this indicates that the model may require further refinement for this particular company. For

ECILC, the errors are similarly concentrated within a narrow range, demonstrating stable performance from the model. Overall, the PSO-ANN hybrid model has shown strong performance characterized by low error densities for most companies; however, the asymmetry and wider spread of the error distribution for DOHOL highlight the need for model optimization to achieve improved results.

Prediction with PSO-SVM

In this study, various parameters of the PSO-SVM model were optimized using Particle Swarm Optimization (PSO) to enhance performance. The optimized parameter values for the PSO-SVM model are presented in Table 16. Specifically, the number of units, activation function, and input shape of the Dense layer were fine-tuned through PSO. Additionally, the parameters C, epsilon, and gamma for Support Vector Regression (SVR) were also optimized using the same method. The optimization process involved a swarm size of 20 and a maximum of 50 iterations to improve the model's performance in predicting stock closing prices, ultimately leading to more accurate predictions.

Table 10. PSO-SVM hybrid model parameters

Parameter	Value
SVR (Support Vector Regression)	C=PSO optimised with, epsilon=PSO optimised with, gamma=PSO optimised with
optimizer	PSO
PSO Swarm Size	20
PSO Max Iteration	50

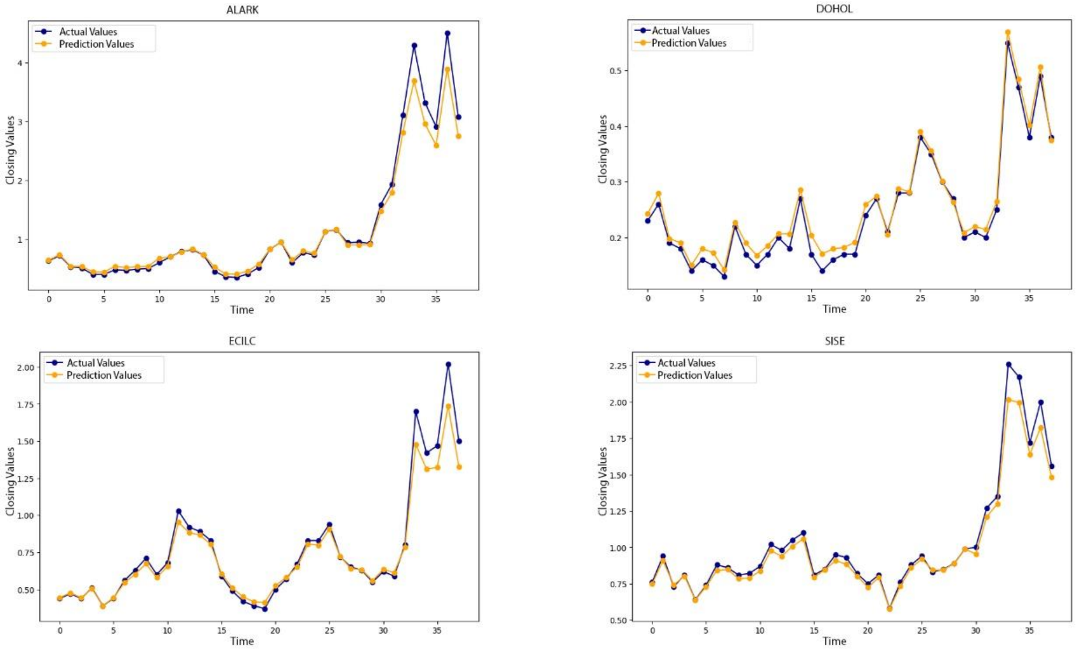
Table 10 outlines the parameters of the SVM (Support Vector Regression) model that has been optimized using the PSO (Particle Swarm Optimization) algorithm. The hyperparameters of the SVR model, specifically C, epsilon, and gamma, were fine-tuned through the PSO method. The optimization process employed a swarm size of 20 particles (PSO Swarm Size) and was conducted over a maximum of 50 iterations (PSO Max Iterations). These parameter settings are designed to identify the most suitable hyperparameters and, in turn, enhance the accuracy of the SVR model.

Table 11. PSO-SVM hybrid model performance results

Companies	MSE	MAE	R^2	MAPE
ALARK	0,0327	0,0978	0,9730	7,0261
DOHOL	0,0003	0,0140	0,9756	6,9330
ECILC	0,0056	0,0420	0,9616	4,2497
SISE	0,0043	0,0408	0,9727	3,2122

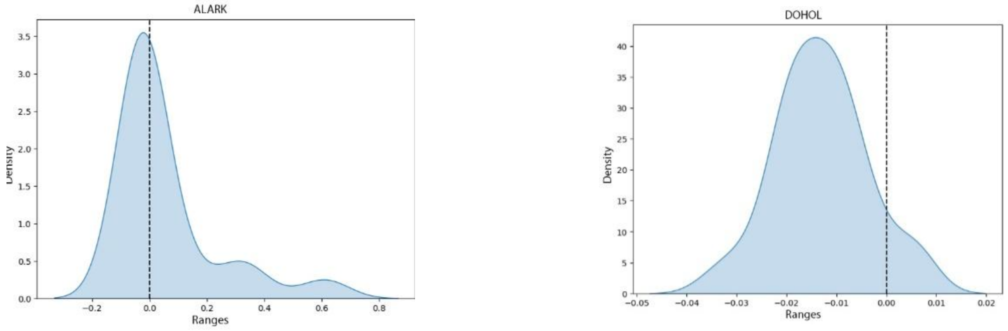
In Table 11, the performance results of the PSO-SVM hybrid model are analyzed. For the ALARK company, while the model achieves a commendable accuracy with an R^2 value of 0.9730, the mean squared error (MSE) of 0.0327 and mean absolute percentage error (MAPE) of 7.0261% suggest that the error rates are comparatively higher than those of other companies. DOHOL has exhibited exceptional performance, recording the lowest MSE (0.0003) and mean absolute error (MAE) (0.0140), along with a high R^2 value of 0.9756. However, its MAPE of 6.9330% points to a slightly elevated error margin relative to its other metrics. ECILC demonstrates satisfactory performance with an R^2 value of 0.9616 and an MSE of 0.0056, alongside a relatively low percentage error rate indicated by a MAPE of 4.2497%. SISE excels with strong predictive performance, highlighting its low MSE (0.0043) and MAE (0.0408) values, along with an R^2 of 0.9727 and a MAPE of 3.2122%, which reflects both model accuracy and minimal error rate. Overall, the PSO-SVM model exhibits successful predictive performance, particularly with SISE achieving the lowest error rates. Improving the error rates for ALARK could result in even better outcomes.

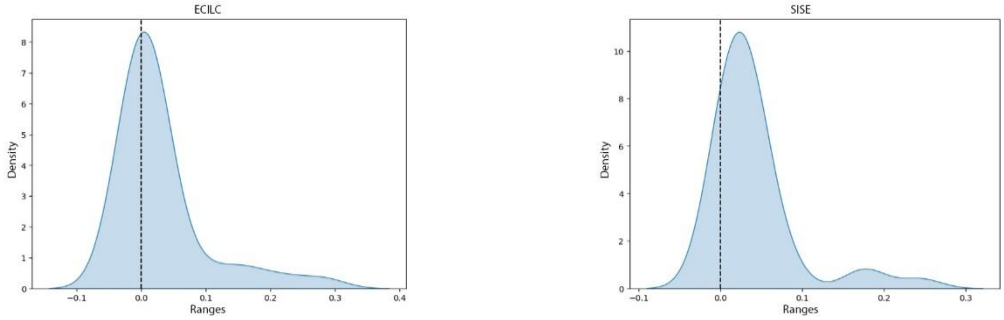
Figure 12. Performance graph of PSO-SVM hybrid model with actual and predicted values



The graphs presented in Fig. 12 illustrate the performance of the PSO-SVM hybrid model by comparing actual and predicted values. For ALARK, the model effectively follows the overall trends, though it displays minor deviations during rapid fluctuations. In the case of DOHOL, the predictions align closely with the actual values despite the dataset's erratic structure, although slight discrepancies occur at the outliers. The results for ECILC reveal that the model accurately tracks general trends in its predictions, despite some minor differences during specific time intervals. For the SISE company, the predicted and actual values are notably similar, indicating a generally stable performance from the model. These graphs demonstrate that the PSO-SVM hybrid model delivers high accuracy across different companies, while also suggesting that enhancements could be beneficial, particularly for ALARK and DOHOL, to improve performance at outlier points. Overall, the model exhibits strong predictive capabilities for each company.

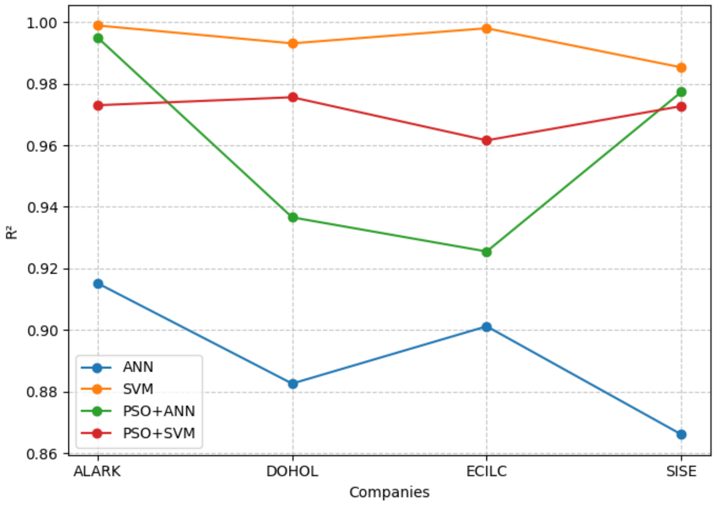
Figure 13. Density plot of companies with PSO-SVM hybrid model





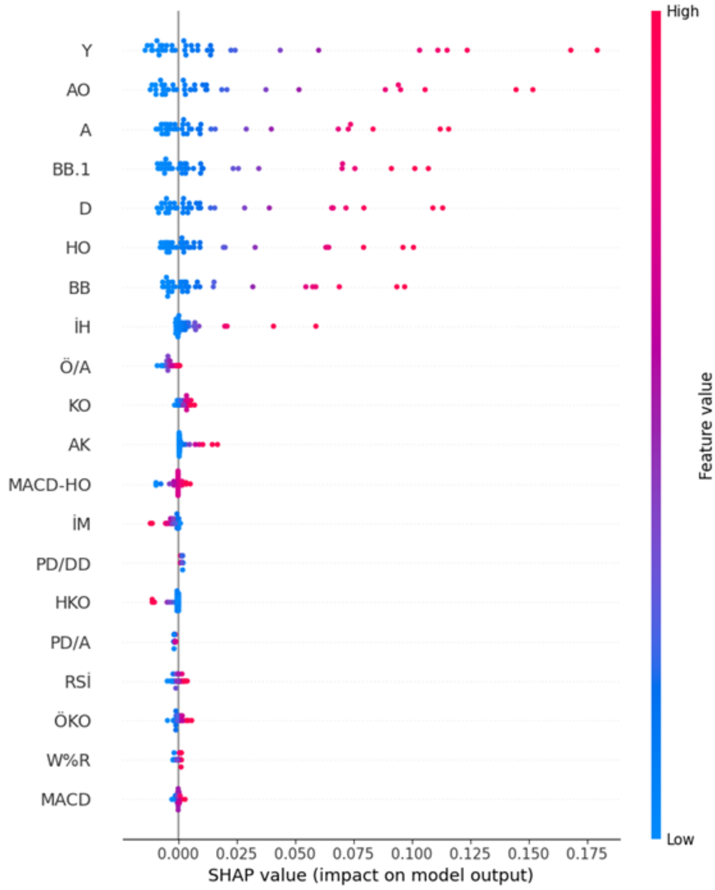
In Fig. 13, the density distributions of forecast errors from the PSO-SVM hybrid model are presented. The concentration of forecast errors for the ALARK and ECILC companies within a narrow range indicates that the model's predictive performance is both consistent and reliable. In contrast, the forecast errors for DOHOL are dispersed over a broader area and exhibit slight asymmetry, suggesting that there is room for improvement in the model's performance for this company. Conversely, for SISE, the symmetric structure and tight density of the error distribution signify that the model yields accurate predictions for this company. Overall, the PSO-ANN model demonstrates effective performance with low error rates for most companies; however, it is advisable to optimize the model for DOHOL due to the observed asymmetry in its error distribution.

Figure 14. Comparison of R2 Values Across Companies and Models



In Fig. 14, the R² performances of four models—ANN, SVM, PSO-ANN, and PSO-SVM are compared across different companies. The SVM model achieved the highest R² values for both ALARK and ECILC companies, indicating superior performance. In other companies, the SVM model consistently outperformed the other models. When comparing the models in general, the SVM model exhibited the highest R² values, signifying its overall effectiveness. The models optimized with PSO (PSO-ANN) showed improved performance compared to the basic ANN model, demonstrating that optimization enhances model performance. Although the ANN model delivered stable results, it was outperformed by both the SVM and PSO-enhanced models. Overall, the SVM model provided the most consistent outcomes, while PSO-supported models offered notable advantages in specific cases, and the ANN model reflected a more average performance.

Figure 15. Impact Levels of Independent Variables on ALARK Stock Closing Price in the SVM Model (20 Variables)



In Fig. 15, the importance levels of the variables concerning their contribution to the model's predictive performance are illustrated through SHAP (SHapley Additive exPlanations) analysis. The high price (Y) and weighted average (AO) emerge as the most influential variables in the model's predictions. Following closely are the opening price (A) and the upper Bollinger band level (BB.1), a recognized technical indicator. Additionally, the low price (D), moving average (HO), and the lower Bollinger band level (BB) also play significant roles in enhancing the model's predictive accuracy. Conversely, the impacts of variables such as the MACD-moving average (MACD-HO), price-to-book ratio (PD/DD), and leverage ratio (KO) are more limited, yielding only a modest contribution to the model's output. Williams %R (W%R) and MACD show the lowest SHAP values, indicating their minimal influence on the model. The color scale within the visualization highlights the effects of each variable, with blue representing low values and red denoting high values, clearly showcasing their contributions to predictive performance. This analysis provides valuable insights for optimizing the model and identifying the most effective variables.

Conclusion

Financial markets play an essential role in enhancing economic growth by facilitating the allocation of capital and steering economic activity. These markets encompass a diverse array of financial instruments, including equities, bonds, derivatives, and insurance products. Enhanced financial literacy has been positively correlated with increased market participation, elevated trading volumes, and a range of overall economic benefits. Analytical methodologies, such as financial time series analyses and machine learning algorithms, serve as indispensable tools for uncovering trends, seasonality, and relationships among various market variables.

The present study investigates the synergistic application of technical indicators, financial ratios, and machine learning models in forecasting stock closing prices. This analysis specifically targets companies categorized under "Financial Institutions / Holdings and Investment Companies" listed on the Borsa Istanbul 100 Index (BIST 100) over a 30-year period, spanning from 1993 to 2023. This research addresses a critical gap in the existing literature by employing advanced methodologies to enhance stock price predictions and deliver actionable insights for investors. Methodologies such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and hybrid Particle Swarm Optimization-enhanced models (PSO-SVM, PSO-ANN) were implemented.

The findings indicate that the PSO-SVM hybrid model exhibited superior overall performance, achieving R^2 values exceeding 0.97 and Mean Absolute Percentage Errors (MAPE) as low as 3.21%. Independently, the SVM model demonstrated robust accuracy, attaining R^2 values of 0.9989 and MAPEs of 1.19%. In contrast, ANN models exhibited moderate performance, with average R^2 values of 0.91 and MAPEs ranging from 7.82% to 13.87%. Furthermore, SHAP analysis was conducted to identify significant variables influencing the predictive outcomes, with high price, weighted average, and Bollinger Bands emerging as the most impactful factors. These results challenge the Efficient Market Hypothesis (EMH), suggesting that machine learning models can effectively synthesize fundamental and technical data to predict stock prices, thereby revealing inefficiencies in weak and semi-strong market forms.

The classification of the companies under examination highlights the specific financial and operational dynamics inherent to the "Financial Institutions / Holdings and Investment Companies" sector. This industry-focused analysis underscores the applicability of the findings to entities with analogous profiles, particularly regarding their financial constructions and market behaviors.

This study contributes to the academic discourse in several significant ways. Firstly, it integrates fundamental and technical indicators with advanced machine learning techniques, thereby establishing a comprehensive framework for stock price forecasting. Secondly, the incorporation of PSO optimization enhances the accuracy of the predictive models, while SHAP analysis augments interpretability by elucidating the most influential variables. These insights effectively bridge the gap between model performance and practical applications in investment strategies.

Despite its contributions, this study is not without limitations. The analysis exclusively targets companies within the "Financial Institutions / Holdings and Investment Companies" category, thus limiting the generalizability of the findings to other sectors. Additionally, macroeconomic factors—such as interest rates, inflation, and geopolitical risks—were not considered, which may diminish the robustness of the models in highly volatile environments. The reliance on quarterly data also constrains the ability to capture intraday or monthly fluctuations, which are pivotal for high-frequency trading.

Future research should endeavor to address these limitations by broadening the scope to include companies across diverse industries and incorporating external macroeconomic and geopolitical variables. Furthermore, the application of advanced machine learning models, such as Gradient Boosting Machines, Long Short-Term Memory (LSTM) networks, or Attention Mechanisms, could be explored to enhance predictive accuracy. The integration of real-time data and testing across various financial markets would also enrich the applicability of the findings. Moreover, employing enhanced explainability techniques—such as LIME—could facilitate deeper insights into variable interactions and model behavior.

In conclusion, this research demonstrates that the integration of technical indicators, financial ratios, and machine learning algorithms, particularly those optimized through PSO, provides a potent framework for stock price prediction. By centering on the financial institutions and holdings sector, the study ingests industry-specific insights while simultaneously challenging the EMH. These findings lay a robust groundwork for future research and offer practical guidance for investors aiming to optimize strategies within dynamic financial markets.

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