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RESEARCH PAPER

Ranking the determinants of financial performance using machine learning methods: an application to BIST energy companies

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Abstract

Energy has been a key driver of change globally. As a developing country, Türkiye's increasing energy demand and consumption highlight the growing importance of efficient and sustainable energy management for its future. This study aims to determine the variables of the financial performance of 12 energy companies. Three different models are created with the return on assets, return on equity, and net profit margin as financial performance indicators of 12 firms. 12 financial ratios are used as input variables as determinants of financial performance. In the analysis, 37 quarterly data between 2014Q4-2023Q4 are used as the sample period. In machine learning, 17 different algorithms are considered in the selection of the appropriate model. The findings indicate that the Bagged Tree algorithm achieved successful outcomes for the ROA target variable, the Boosted Tree model demonstrated effective performance for the ROE model, and the Linear SVM algorithm yielded favorable results for the NPM model. According to the result obtained by the LIME method, Liquidity Ratio and Cash Ratio affect the ROA, ROE, and NPM models positively, while inventory turnover affects the models negatively.

Keywords: Machine learning; financial performance; BIST; energy firms

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1 Introduction

Energy has been one of the important building blocks of many changes in the world and still maintains this feature. Energy and energy use are the main factors affecting the economic and

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socio-cultural change of countries [1]. As a result of population growth, industrialization and urbanization in the world, the amount of trade and production has increased as a result of globalization. Accordingly, the demand for natural resources and energy is increasing [2]. Energy has many uses such as home, workplace, transportation, heating, lighting and industry. Today, the use of new technologies that need energy in the production and consumption process of many goods and services increases energy consumption [3]. The use of energy resources has also increased due to the increase in production, especially after the Industrial Revolution. The search for raw materials for the energy that feeds the industry has changed the strategies of the countries, wars have broken out and energy has become a source of power [4].

Energy is defined as the ability to do work. Energy sources are subject to several classifications such as primary and secondary, conventional, unconventional and renewable, and non-renewable energy sources [5, 6]. The most widely used classification is the classification of energy sources as renewable and non-renewable energy sources according to their use. Non-renewable energy sources are divided into two sources as fossil-based energies and nuclear-based energies [7]. Primary energy sources such as oil, gas, and coal are limited in nature. Consumption of a limited resource means a decrease in future consumption. Renewable energy sources such as wind, solar, hydro, and geothermal, on the other hand, refer to resources that can renew themselves and remain depleted in the future [8, 9].

For economic development and sustainable growth, it is important to have sufficient energy resources and to ensure energy supply security [10]. Efficient and sustainable management of energy resources is of great importance in terms of both economic development and environmental sustainability.

Today, fossil energy sources are mainly used in energy supply. Fossil fuels account for about 80% of the world's energy supply in 2023. According to the estimates of international energy organizations, the ratio of fossil resources in energy consumption will be in the first place until 2040 [11]. The cost advantage of fossil fuels and their use habits from the past have led to a high share in energy use. Considering the amount of use of fossil fuels, the current reserve amounts will be insufficient to meet the increasing energy demand in the future. In addition, the use of fossil fuels leads to significant environmental problems [12]. With the Paris Agreement of 2016 and the EU Green Deal, some limitations have been put forward in the use of fossil-based energy to manage climate and environmental problems [13, 14]. For all these reasons, the trend towards renewable energy sources instead of fossil fuels has increased in resource use. The importance of renewable energy sources is increasing day by day because they are clean, reliable and sustainable. To benefit from the economic and environmental positive externalities of renewable energy sources, countries subsidize the use of renewable energy sources in energy production instead of fossil resources [15].

Between 2013 and 2023, fossil fuels' share in the global energy mix dropped from 82% to 80%. Over this time, global energy demand grew by 15%, with 40% of this rise being met by clean energy [16]. The International Energy Agency forecasts that global energy demand will rise by at least 25% by 2040. From 2010 to 2023, there was a 20% increase in world energy supply [16]. Fossil fuels account for approximately 82% of Türkiye's energy supply in 2023. From 2010 to 2023, there has been a 50% increase in Türkiye's energy supply [17]. While Türkiye's energy consumption was approximately 78 Mtoe in 2000, it reached 168 Mtoe by 2023. Türkiye's energy consumption has nearly doubled in the last 23 years. By 2035, the annual increase in average energy consumption is projected to be 2.2%. It is estimated that the installed capacity of electricity, which was 95.9 GW in 2020, will increase to 189.7 GW by 2035. It is thought that the share of renewable energy sources, which was 52.0% in the installed capacity in 2020, will reach 64.7% by 2035 [19]. In Türkiye's Twelfth Development Plan, energy has been taken into account in the priority development area.

As a target, it aims to maximize self-sufficiency in energy by evaluating domestic and renewable energy sources based on net zero emissions in 2053.

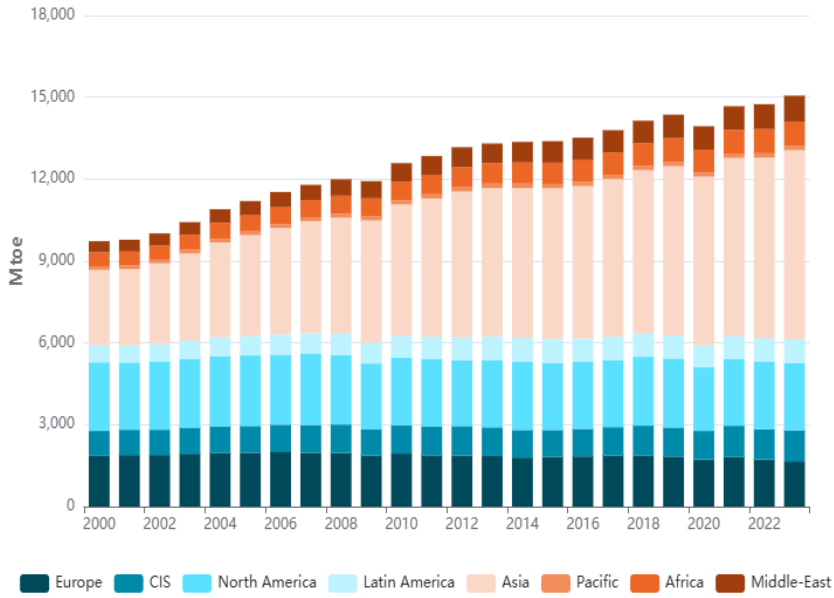

Figure 1. 2000-2023 World Energy Consumption (Mtoe) [18]

While the world's energy consumption was approximately 9725 Mtoe in 2000, it reached 15061 Mtoe by 2023. The world's energy consumption has increased by approximately 54% in the last 23 years.

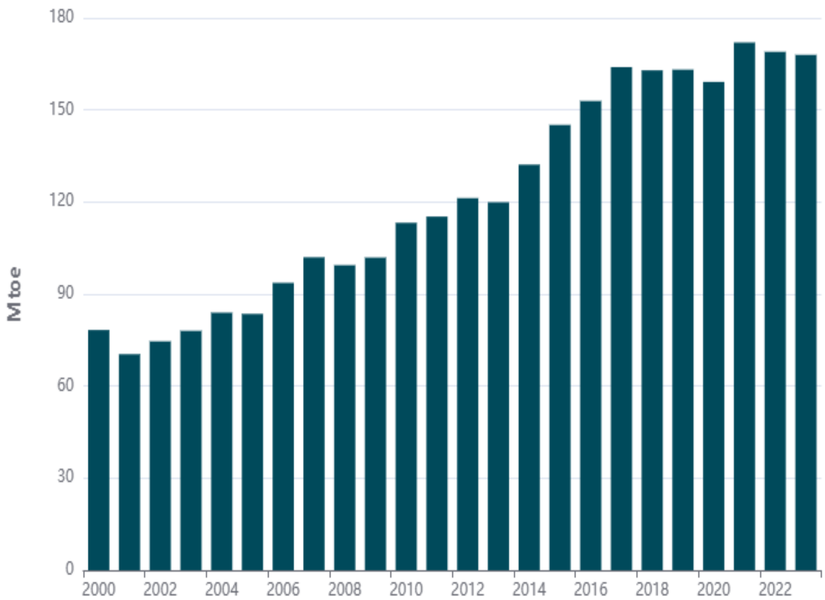

Figure 2. 2000-2023 Türkiye's Energy Consumption (Mtoe) [18]

Türkiye has an increase in both energy supply and energy consumption, above the increase in the world average. This is an indication that the energy sector will become more and more important for Türkiye. Türkiye is significantly reliant on imported energy sources, including crude oil and natural gas, to meet its industrial and economic demands. This reliance makes Türkiye vulnerable to fluctuations in global energy markets, impacting industrial production costs and market behavior [20]. For this reason, the performance of companies operating in the energy sector is important for the successful development of the sector.

In Türkiye, which is one of the developing countries, the energy sector has developed as in other sectors due to the increase in population, industrialization and economic volume [21]. Türkiye is an important country in terms of energy production and consumption. Türkiye, which is an energy corridor due to its geographical location, plays a strategic role both as an energy importer and as an energy transit country [22].

As a result of the liberalization policies in the Turkish economy in the 1980s, private enterprise's investments in the energy sector began to increase. EMRA was established in 2001. EMRA, as a public authority, is to regulate and supervise the provision of energy to the consumer in a sufficient, high quality, continuous, economical and environmentally friendly manner. With the establishment of EMRA, competitiveness and transparency in the energy market have increased. Over time, the interest of private enterprise in the energy sector has increased. Recently, interest in the renewable energy sector has increased due to its economic and environmental impacts. Noticing the increasing interest of investors, companies have been included in the stock markets with public offerings. 5 energy companies went public in 2022, 9 in 2023 and 2 in 2024 [23]. The increasing number of companies in the energy sector has brought competition with it. In order to keep up with this competition, companies try to keep their financial performance indicators at a high level [24]. Energy companies that are strong in terms of financial performance will ensure that the sector is strong and sustainable in the future. It would be appropriate to determine the financial performance of the energy sector, which makes a great contribution to the economies of the countries.

The number of companies traded on BIST is 48. 35 of these companies carry out energy production and distribution activities, and 13 of them are companies that develop energy technologies. The total market value of 48 companies is 810 billion TL. As of the end of 2023, the total assets of 48 companies are 1,317 billion TL, net sales are 690 billion TL and the total number of employees is approximately 42 thousand people. There are 12 energy companies in BIST 100 [25, 26]. There are 33 energy companies in the Electricity Index (XELKT) in BIST [27].

The objective of this study is to explore the determinants of the financial performance of 12 energy firms operating on Borsa Istanbul. Three different models were created with the return on assets, return on equity and net profit margin as financial performance indicators of 12 firms. 12 financial ratios were used as input variables as determinants of financial performance. In the analysis, 37 quarterly data between 2014Q4-2023Q4 were used as the sample period. Machine learning algorithms were used in the selection of the appropriate model. As a measure of financial performance, 17 different algorithms were run for return on assets, return on equity and net profit margin. The ideal method was selected for each financial performance measure. According to this method, the importance of independent variables for financial performance has been revealed.

In the introduction part of the study, information about energy types in general, energy supply and consumption in the world and also Türkiye, and energy companies in Borsa Istanbul are included. In the theoretical part of the study, the relationship between financial performance, financial ratios and financial performance with the machine learning method was revealed. In the literature part of the study, studies on the determinants of profitability in energy companies and the relationship between financial performance and machine learning are included. In the Method part of the study, test statistics were explained to the data set. In the analysis and findings part of the study, the results of machine learning methods are included. In the conclusion and suggestions section, the findings of the study were interpreted by comparing them with the results of the study in the literature.

2 Conceptual framework

Businesses should create a proper financial information system in order to continue their activities uninterruptedly in changing market conditions. Then, the collected financial information is evaluated about the business by using a number of analytical techniques within the scope of financial analysis, which is one of the basic functions of financial management [2].

Financial performance importance for firms

Performance is the measurement of the parameters of achieving a goal [28]. Financial performance is used in the process of measuring the results of businesses related to money. The financial performance of the companies allows for the evaluation of their past activities and provides insights into their future decisions by analyzing information on liquidity, financial structure, asset utilization, and profitability [29].

One of the commonly used methods in measuring financial performance is ratio analysis. The ratio mathematically indicates the relationship between two numbers. The financial ratio, on the other hand, refers to the relationship between two items in the financial statements. The main purpose of ratio analysis is to interpret the relationship between two items in the financial statements [30]. Ratio analysis focuses on different dimensions of performance, with each ratio representing a specific factor. It is employed to evaluate the relative relationships of the values in the financial statements prepared by businesses, which are based on their activities and provide financial information [31].

By using financial ratios, the strengths and weaknesses of businesses are determined in basic issues such as financial structure, liquidity, profitability, and growth [32]. With the help of financial ratios, the current status of the enterprises can be compared with their past performance as well as with the averages of the sector in which the business is located [33, 34]. In addition, it is checked whether the budget targets are met by using financial ratios [29]. Financial ratios have a wide range of users, such as business financiers, business managers, current or potential partners, financial analysts, and academic researchers [35].

Profit is the main goal of a business. Profit provides evidence about a firm's earning potential and how efficiently a company is managed. Companies need to make a profit in order to grow and continue their activities without interruption. If companies cannot make a profit, their existing capital will erode after a while and companies may go bankrupt if the loss situation continues. No one invests in companies that do not make a profit or make less profit than their competitors and do not want to provide financing.

Machine learning and financial performance relationship

Machine learning (ML) has transformed the financial industry by offering advanced predictive capabilities and enabling the development of robust financial performance models. The relationship between ML and financial performance lies in the ability of ML algorithms to process large volumes of complex financial data, extract meaningful patterns, and provide actionable insights to enhance decision-making. ML models significantly outperform traditional statistical methods in predictive accuracy, making them indispensable in navigating the complexities of modern financial data [36].

ML techniques have demonstrated the ability to accurately predict key financial metrics, such as profitability, market trends, and corporate financial risk. For instance, random forest models have been used effectively to predict profitability, outperforming traditional statistical methods in accuracy and reliability [37]. Furthermore, algorithms like LSTM are adept at capturing temporal dependencies within financial data, making them ideal for trend forecasting in volatile markets [38].

The predictive capabilities of ML directly contribute to financial performance by improving forecasting accuracy, enabling risk mitigation, and optimizing resource allocation. For example, ML frameworks that integrate technical and economic indicators offer better interpretability and allow firms to make informed decisions that enhance profitability and reduce risks [39].

Feature selection is a critical component of ML frameworks, ensuring that only the most relevant data are utilized to optimize model performance. Studies have shown that constructing higher-level features, such as financial ratios derived from domain knowledge, significantly improves the accuracy of financial performance predictions [40]. These selected features enable ML models to focus on key financial determinants, thereby enhancing their predictive power and practical relevance.

Dynamic feature selection methods have further strengthened the relationship between ML and financial performance by adapting to changing market conditions. For instance, models employing local shuffling techniques dynamically prioritize the most impactful features, ensuring that predictions remain accurate even in fluctuating financial environments [41].

3 Literature review

This section covers the factors influencing profitability in energy companies, their financial performance, the role of machine learning, and the connection between profitability and machine learning in the energy sector.

The determinants of profitability in energy companies

Goto and Sueyoshi (2009) discussed whether there is a financial difference between the companies that provide electricity and both electricity and gas in the USA and how to make financial performance rankings, and as a result of the study, return on equity in profitability, long-term foreign resources to equity in leverage, current ratio in liquidity were determined as important financial ratios to distinguish companies [42]. Ekatah et al. (2011) examined the relationship between CSR and profitability of the Royal Netherlands Shell PLC in their case study; statistical and trend analysis and as a result of the study, they found a positive relationship between CSR and profitability [43]. Hughey and Sulkowski (2012) tested the profitability of 45 energy sector companies with regreyon analysis, and the study concluded that the more information available about the businesses, the better their reputation [44]. Gozbası and Aslan (2015) examined 13 Turkish energy companies in order to measure the permanence of profit in the energy sector with panel data analysis, it was concluded that price competition was weak, retail volume was low and profit permanence was high [45]. İskenderoğlu et al. (2015) analyzed the financial statement values of the Turkish energy sector and the European energy sector in terms of liquidity, financial structure, efficiency and profitability with the ratio analysis in their study, and as a result of the study, it was concluded that the enterprises in the European energy sector were better in these table values [2]. Fareed et al. (2016) examined the variables affecting the profitability of firms in the electricity and power sector in Pakistan by panel data analysis method and as a result, they found that firm size, sales growth and electricity crisis had a positive effect on asset return, while firm age, leverage ratio and efficiency variable had a negative effect on asset return [46]. Esmeray and Esmeray (2016) examined the firm profitability of Turkish Energy Companies with panel data analysis and as a result of the study, they concluded that total debt, equity and net sales had a positive effect on net profit [47]. Eyüboğlu and Çelik (2016) analyzed the financial performances of Turkish energy companies with Fuzzy Analytical Hierarchy and Fuzzy Topsis Method, and as a result of the study, it was determined that Zoren company had the worst performance [48]. Metin et a. (2017) measured the performances of energy companies traded in Borsa Istanbul with Topsis and Moora techniques and compared the results, and as a result of the study, it was determined that the financial performances of the companies varied [49]. Erduru (2018) analyzed the financial structure and performance of the electrical energy generation and distribution sector in Türkiye with the ratio analysis method, and as a result of the study, it was determined that the liquidity ratios realized in the sector were below the standard rates [50].

Klimenko et al. (2018) analyzed the profitability determinants of thirty-seven energy companies on the Thai Stock Exchange with Least Squares (OLS) models, and as a result of the study, they concluded that the size of the firm negatively affects their profitability, financial liquidity affects profitability positively, and the firm's income affects profitability positively [51]. Apan and Islamoglu (2018) examined the effect of financial ratios such as liquidity, financial structure, efficiency and profitability on the return on assets of 10 energy companies traded on the BIST with panel data analysis, and as a result of the study, it was determined that the asset turnover ratio and liquidity ratio were statistically significant and positive, and the financial leverage ratio, "tangible fixed asset/asset" and "long-term debt/asset" ratios negatively affected the return on assets [1]. Bağcı and Yüksel Yiğiter (2019) analyzed the financial situation of 15 energy companies registered in BIST using the standard deviation and Waspas Method, and as a result of the study, it was determined that the company with high financial performance changed every year [52]. Karcıoğlu et al. (2020) analyzed the financial performances of energy companies traded on BIST using Intuitive Fuzzy Logic and Multi-Criteria Decision Making Techniques, and as a result of the study, the ranking of the best performing and non-performing companies was determined through the techniques used [53]. Ghani et al. (2023) conducted a panel data analysis of the factors affecting the capital structure of energy sector firms operating in Pakistan, India, Bangladesh and Sri Lanka. According to the results, it was revealed that the profitability variable is the most effective variable on the capital structure [54].

Financial performance and machine learning

Yıldırım et al. (2011) tested the financial return of the paper industry in Türkiye with artificial neural networks and multiple linear regression methods. They found that the artificial neural network had better performance [55]. Manojlovic and Stajduhar (2015) created a model to predict the trend of 4 stocks on the Zagreb Stock Exchange using random forest logarithms. They have achieved successful results in predicting the trends of the stock market [56]. Tekin and Çanakoğlu (2018) investigated the estimation of stock returns of 25 companies in Borsa Istanbul by various methods. From these models, they found that the random forest algorithm gave the best results [57]. Bhardwaj and Akil Ansari (2019) compared various algorithms to evaluate stock prices in the future to analyze market behavior and reach the best performance from these models with logistics regression algorithms [58]. Vijh et al. (2020) analyzed the forecast of future stocks of 5 different sectors with ANN and RF, and as a result of the study, they concluded that ANN made better predictions [59].

Öztürkmen and Eren (2020) predicted the price rise and fall of the BIST100 index with 15 different algorithms, and as a result of the study, they concluded that Light Gradient Augmenting Machines (LightGBM) provided the best performance among these algorithms [60]. Roy et al. (2020) tested the stock prices of companies traded on the KOSPI Index in Korea with various algorithms. They achieved the lowest performance with the deep learning method [61]. Koç Ustalı et al. (2021) tested the stock price predictions of the companies in the BIST-30 index with algorithms. They concluded that ANN, random forest algorithm and extreme gradient augmentation (XGBoost) methods were successful [62]. Arslankaya and Toprak (2021) analyzed the price prediction of Ereğli iron and steel stock with the help of algorithms. As a result, the most successful algorithm was Random Forest Regression [63]. Reddy and Kumar (2022) compared gradient boosting machines (CPVs) and support vector machines (SVM) for stock price prediction and concluded that the gradient boosting machine model was more successful [64]. Hu et al. (2022) performed performance comparisons for 3 stocks using Light Gradient Boosting Machines, Random Forest, and Logistics Regression. As a result, the models obtained different results in the short and long term [65]. Leippold et al. (2022) analyzed the predictive power of the Chinese stock market using different machine learning methods. As a result of the study, they concluded that the application of machine learning was successful [66].

Nakagawa and Yoshida (2022) used different methods in stock forecasting. He concluded that the time-series gradient boosting tree was superior to previous working methods [67]. Shrivastav (2022) used different models for stock market return forecasting. He concluded that the ensemble model worked better than other models [68]. Akyol Özcan (2023) predicted the increases and decreases of stock market indices with machine learning algorithms. As a result, it was concluded that the random forest algorithm obtained high results in the training data and low results in the test data [69]. Hartanto et al. (2023) tested their stock price predictions using the LightGBM algorithm, and the result of the analysis was that the CPV version performed better [70]. Kesharwani et al. (2023) applied a machine learning model to predict stock asset prices, and as a result, the most accurate model is the Gradient Boosted Regressor model [71]. Toprak et al. (2023) tested the stock prices of Petkim Petrochemical Holding with different models. They concluded that algorithms can be used to predict stock prices based on their coefficients of determination [72]. Rastogi et al. (2020) used machine learning techniques to analyze the trend in the financial performance of large renewable energy companies in India and the United States using return on equity (ROE). As a result of the study, it was concluded that the performance of companies in the renewable sector is largely affected by government policies [73].

4 Determining the variables for the problem

In this study, 37 quarterly data of 12 energy companies traded in Borsa Istanbul between 2014Q4 and 2023Q4 in Table 1 were used. Financial information of the companies was obtained from Finnet, Fintables and KAP databases [25–27].

Table 1. Energy companies using data in analysis

Number	Company Code	Number	Company Code
1	ORGE	7	AYEN
2	SAYAS	8	ZOREN
3	AKENR	9	YAYLA
4	AKSEN	10	ODAS
5	AKSUE	11	PRKME
6	ALARK	12	ZEDUR

The variables used in the analysis are given in Table 2. There are 3 target variables in the analysis. The other 12 variables are input variables.

Table 2. Variables determination

Variables Type	Variables Description	Variables Formula
Input Variables	Current Ratio	$=\frac{\text{Current Assets}}{\text{Current Liabilities}}$
	Liquidity Ratio	$=\frac{\text{Current Assets}-\text{Inventory}}{\text{Current Liabilities}}$
	Cash Ratio	$=\text{Cash}/(\text{Current Liabilities})$
	Total Debt Ratio	$=\frac{\text{Total Assets}-\text{Total Equity}}{\text{Total Assets}}$
	Financing Ratio	$=(\text{Total Equity})/(\text{Total Liabilities})$
	Receivables Turnover	$=(\text{Net Sales})/(\text{Average Accounts Receivable})$
	Inventory Turnover	$=(\text{Cost Of Good Sold})/(\text{Average Inventory})$
	Accounts Payable Turnover	$=\frac{\text{Supplier Purchases}}{\text{Average Accounts Payable}}$
	Current Asset Turnover	$=(\text{Net Sales})/(\text{Average Total Assets})$
	Asset Growth	$=\frac{\text{Present Assets Value}-\text{Past Assets Value}}{\text{Past Assets Value}}$
	Price/Earnings (P/E)	$=\frac{\text{Stock}'\text{S Current Price}}{\text{Earning Per Share (EPS)}}$
	Market Value / Book Value (MV/BV)	$=\frac{\text{Stock}'\text{S Current Price}*\text{Number Of Shares}}{\text{Total Assets}-\text{Total Liabilities}}$
Target Variables	Return on Assets (ROA)	$=(\text{Net Income})/(\text{Total Assets})$
	Return on Equity (ROE)	$=(\text{Net Income})/(\text{Total Equity})$
	Net Profit Margin (NPM)	$=(\text{Net Income})/(\text{Net Sales})$

5 Methods

Machine learning methods offer advantages over classical techniques due to their ability to model complex relationships, process high-dimensional data, enhance prediction accuracy, provide flexible modeling approaches, and incorporate explainable artificial intelligence (XAI). The primary objective of employing machine learning algorithms is to achieve flexible modeling and to investigate the interpretability of the model generated by artificial intelligence. A similar analysis could also be conducted using panel data analysis. However, panel data analysis typically relies on predefined structural assumptions, such as fixed effects or random effects, which may pose a limitation in fully capturing the complexity of real-world data. In the study, the cross-validation method was employed. Accordingly, the dataset was not divided into separate training and test sets; instead, all data were iteratively used for both training and testing. Therefore, a proportional split between training and test datasets was not implemented in this study. In the study, the dataset was trained using various algorithms, including neural networks, ensemble methods, support vector machines, and linear models, and the algorithm demonstrating the best performance was identified. This section elaborates on the theoretical framework of the bagged and boosted trees, linear SVM, which exhibited the highest performance in the model, as well as the LIME algorithm, which was employed for variable interpretation in this research.

Bagged trees (bootstrap aggregating trees)

Bagging is based on the principle of training multiple decision trees in parallel and aggregating their predictions. It offers advantages in reducing overfitting and lowering variance [74, 75].

Step 1: Bootstrap Sampling: From the dataset, B bootstrap samples of size n are drawn. Each bootstrap sample is randomly selected from the original dataset with replacement. For each bootstrap sample $D_b(b=1,2,\ldots,B)$, a decision tree T_b is trained.

Step 2: Aggregation of Predictions: For regression problems, the predictions obtained from each sample are averaged.

$$\hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x). \tag{1}$$

Here, $\hat{f}_{bag}(x)$ represents the aggregated prediction for the input x, B denotes the number of bootstrap samples, and $T_b(x)$ corresponds to the prediction of the $b-th$ decision tree. This averaging process helps to stabilize the predictions and reduce variance, thereby enhancing the model's generalization performance.

Boosted trees (Gradient boosting trees)

Boosting is based on the principle of sequentially training weak learners and correcting the errors of the previous steps at each iteration. Gradient boosting is the most common variant of this method. It is effective in balancing bias and variance and modeling complex relationships [76]. The implementation is carried out in five steps, which are as follows:

Step 1: Initialization of the Model: Initially, a constant prediction $F_0(x)$ is made. For example, in regression, this could be the mean of the target variable:

$$F_0(x) = argmin_{\gamma}^{\sum_{i=1}^{n} L(y_i,\gamma)}. \tag{2}$$

Here, $L(y_i, \gamma)$ represents the loss function, and γ is the constant value that minimizes the loss, typically the mean of the target values for regression tasks. This initial model serves as the baseline for subsequent iterations.

Step 2: Calculation of Residuals: At each step $m = 1, 2, \ldots, M$, the errors (residuals) of the previous model are computed. The residuals represent the difference between observed values and the predictions made by the current model. Specifically, the residuals r_{im} for each observation i are calculated as follows:

$$r_{im} = -\left[\frac{\partial L\left(y_i, F_{m-1}^{(x_i)}\right)}{\partial F_{m-1}^{(x_i)}}\right]. \tag{3}$$

Here, y_i is the observed target value, $F_(m-1)(x_i)$ is the prediction from the model at the previous step $m-1$, and r_{im} is the residual for the $i-th$ observation at step m. these residuals are used as the target values for training the next weak learner in the sequence.

Step 3: Training the Tree: A decision tree $h_m(x)$ is trained on the residuals. The goal of this step is to fit a model that captures the patterns in the residuals, thereby improving the overall predictive performance. Mathematically, this can be expressed as:

$$h_m(x) = argmin_{h}^{\sum_{i=1}^{n}(r_{im}-h(x_i))^2}. \tag{4}$$

Step 4: Updating the Model: The new model is updated by combining the previous model with the weighted sum of the newly trained tree. The update is performed as follows:

$$F_m(x) = F_{m-1}(x) + v.h_m(x). \tag{5}$$

Here, $F_m(x)$ represents the updated model at step m, $F_{m-1}(x)$ is the model from previous step,

$h_m(x)$ is the decision tree trained on the residuals, and v is learning rate (a small positive value $0 < v \leq 1$). This iterative update continues until the specified number of iterations M is reached.

Step 5: Prediction: The final model $F_M(x)$ is used to make predictions. After completing all M iterations, the model $F_M(x)$ represents the ensemble of all weak learners (trees) trained in the boosting process. The prediction for a given input x is obtained as follows:

$$F_M(x) = F_0(x) + v. \sum_{m=1}^{M} h_m(x). \tag{6}$$

Here, $F_0(x)$ is the initial model, v is the learning rate and $h_m(x)$ are the decision trees trained at each step m. This step concludes the gradient boosting process, and the model is ready for deployment or evaluation [77].

Linear support vector machine

The Linear SVM (Support Vector Machine) method is used for both classification and regression tasks [78]. The implementation of regression is carried out in five steps, which are as follows;

Step 1: Problem Definition: Let the dataset donated as $\{(x_i, y_i)\}_{i=1}^{n}$ where $x_i \in R^d$ represents the feature vector and $y_i \in R$ represents the target variable. The objective in this step is to find a hyperplane of the $w.x + b = 0$, where w is the weight vector and b is the bias term. This hyperplane serves as the foundation for the regression model, aiming to minimize the prediction error while maintaining generalization.

Step 2: Epsilon Tube: SVM constructs an epsilon tube around the target values. This tube defines the acceptable margin of error for predictions. If a prediction lies within this tube, it is considered acceptable; otherwise, it is not. The hyperplane equation is given by:

$$f(x) = wx + b. \tag{7}$$

The epsilon tube is defined by the constraints:

$$y_i - (wx_i + b) \leq \varepsilon \text{ and } (wx_i + b) - y_i \leq \varepsilon. \tag{8}$$

Here, ε represents the maximum allowable deviation from the predicted value.

Step 3: Soft Margin: If the data does not fit within the epsilon tube, a soft margin SVR is employed. In this case, slack variables ξ_i and ξ_i^* are introduced to allow for errors. The optimization problem is formulated as follows:

$$min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*). \tag{9}$$

Here C is a regularization parameter that controls the trade-off between minimizing the model complexity $\|w\|^2$ and penalizing errors ξ_i and ξ_i^*. Subject to the constraints:

$$y_i - (wx_i + b) \leq \varepsilon + \xi_i, \qquad \forall i = 1, 2, \ldots, n, \tag{10}$$

$$(wx_i + b) - y_i \leq \varepsilon + \xi_i^*, \qquad \forall i = 1, 2, \ldots, n, \tag{11}$$

$$\xi_i, \xi_i^* \geq 0, \qquad \forall i = 1, 2, \ldots, n, \tag{12}$$

Step 4: Lagrange Multipliers and Dual Problem: The optimization problem from the previous step is transformed into its dual form using the method of Lagrange multipliers. The dual problem is formulated as follows:

$$max_{\alpha,\alpha^*} \sum_{i=1}^{n} y_i(\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(x_i x_j). \tag{13}$$

Constraints:

$$0 \leq \alpha_i, \alpha_i^* \leq C, \quad \forall i = 1, 2, \ldots, n, \tag{14}$$

$$\sum_{i=1}^{n} (\alpha_i - \alpha_i^*) = 0. \tag{15}$$

Here α_i ve α_i^* are the Lagrange multipliers with the constraints.
Decision Function: After training, predictions for a new example x are made using the decision function which is given in Eq. (7). This step concludes the prediction process, enabling the model to generalize to unseen data.

LIME (Local Interpretable Model-Agnostic Explanations) model

Machine learning techniques are often regarded as "black-box" models. This implies that the details of the algorithm cannot be explained as a mathematical model, as is the case with classical techniques. However, through methods such as LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations), the model can be interpreted using local approximations. Ultimately, the impact of each input on the output can be numerically interpreted. However, it is known that this approach is only valid for local data, which may pose a challenge in generalizing the model from the obtained insights. Therefore, the coefficients are evaluated solely as an indicator of importance and interpreted accordingly.

LIME is a technique designed to make the predictions of any machine learning model locally interpretable. It is used to understand the “black-box” behavior of complex models. The core idea of LIME can be interpreted in three main steps: sampling (creating a local dataset), modeling (training a simple model on the local dataset), and explanation (using the coefficients of the simple model to explain the predictions of the original model).

Mathematically, the explanation can be represented as:

$$\xi(x) = argmin_{g \in G} L(f, g, \pi_x) + \Omega(g), \tag{16}$$

where:

- x: Sample
- f: Original model (black-box)
- g: Simple interpretable model,
- L: Loss function measuring how well g approximates f in the local region,
- π_x: Proximity measure defining the locality around the instance x,
- $\Omega(g)$: Regularization term to ensure the simplicity of g.

LIME provides a powerful framework for interpreting complex models, making it a valuable tool for understanding and validating machine learning predictions.

6 Analysis and findings

This study aims to predict the factors affecting profitability in energy companies using artificial intelligence algorithms and to determine the impact levels and importance rankings of the financial ratios used as inputs. In this direction, a literature review was first conducted to create variables and a conceptual framework. Then, the variables were identified, and the target variable (profitability ratios; ROA, ROE and NPM) was predicted according to machine learning algorithms. Separate models were produced for three different profitability ratios. Subsequently, the algorithm that yielded the most successful results was identified, and the importance levels of the variables were determined using LIME. In the final section of the study, the findings obtained were interpreted comparatively.

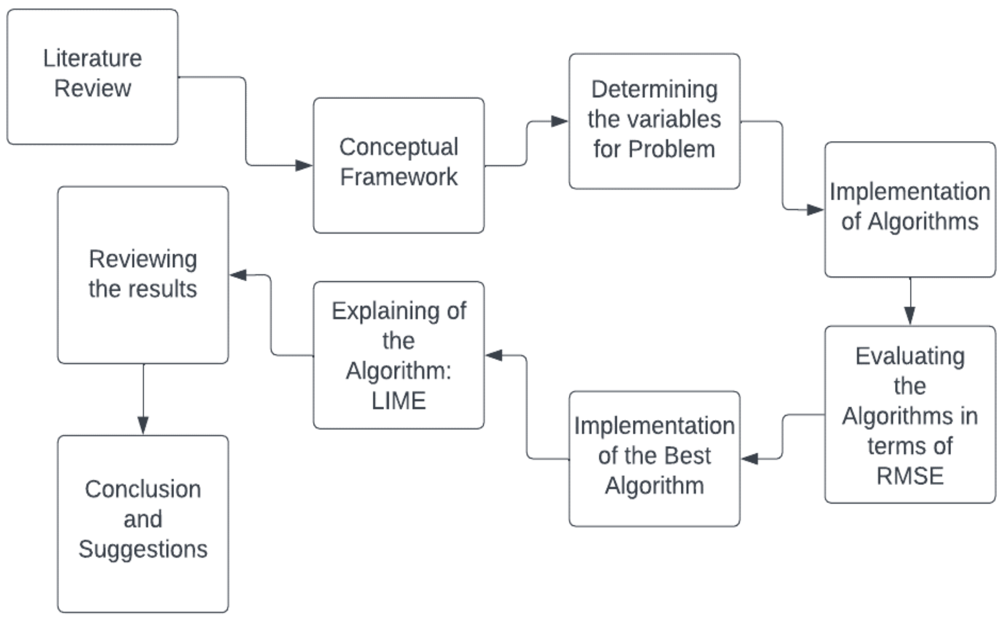

Figure 3. Flowchart of the study

Application of algorithms and identification of the most successful algorithm

In this section of the study, all machine learning algorithms that can be used to predict the ROA, ROE and NPM target variables related to the variables determined in the previous section have been applied. The main aim here is to determine which algorithm produces successful results. In this regard, the application was performed as 5-fold cross-validation. The results obtained are shown in Table 3 and Table 4.

As can be seen in the table, a total of 17 algorithms have been studied based on 4 main ones. As a result, it has been observed that the Bagged Trees algorithm produced the lowest error for the ROA target variable; the Boosted Tree model for the ROE target variable; and the Linear Support Vector Machine algorithm for the NPM target variable. The results obtained from the application of the algorithms are as follows:

As a result of the algorithm application, the R2 value has been determined at levels of 60%, 50%, and 6%. According to the obtained results, it is seen that the algorithms explain the ROA and ROE target variables at a more sufficient level. However, it is difficult to say that the algorithms are successful in predicting the model for the NPM target variable.

Table 3. Algorithms used in target variable prediction and success levels

Algorithm	Method	RMSE Value for ROA	RMSE Value for ROE	RMSE Value for NPM
Neural Network	Narrow NN	26.37	479.59	54772.24
	Medium NN	27.24	909.61	1427782.72
	Wide NN	39.70	795.48	1256325.72
	Bilayered NN	17.45	145.21	694552.26
	Trilayered NN	49.2	228.71	864163.15
Ensemble	**Boosted Trees**	9.75	**10.75**	93447.98
	Bagged Trees	**9.61**	94.25	51127.74
Support Vector Machine	**Linear SVM**	12.82	101.98	**51052.02**
	Quadratic SVM	228.05	147.24	52485.72
	Cubic SVM	6513.7	7042.2	52257.60
	Fine Gaussian SVM	16.56	102.93	263942.56
	Medium Gaussian SVM	13	101.09	52505.28
	Coarse Gaussian SVM	13.05	103.12	52502.60
Linear	Linear Regression	12.65	101.1	52500.09
	Interactions Linear	31.67	254.8	59022.11
	Roboust Linear	12.80	103.1	130390.17
	Stepwise Linear	16.01	119.13	52497.63

Table 4. Evaluation measurement results of algorithms that make the most successful predictions

Measure Type	Method 1: Bagged Tree	Method 2: Boosted Tree	Method 3: Linear SVM
RMSE	9.61	10.75	51052
R-Squared	0.6	0.5	0.06
MSE	92.4	115.46	2.6063e+09
MAE	5.97	6.02	8409
Prediction Speed	6200 obs/sec	7700 obs/sec	6200 obs/sec
Training Time	3.95 sec	2.06 sec	2.24 sec
Model Size	404 kb	187 kb	179 kb

Determining the importance levels of variables using The LIME technique

The LIME technique is a tool used to understand and interpret the predictions of complex machine learning algorithms. It has advantages such as clarifying model behavior, identifying important variables, and assessing model reliability. However, a disadvantage of the method is that the information obtained may not always be generalizable due to the examination of only a portion of the data. In this section, it is aimed to determine the importance levels of the input variables of the model obtained as a result of the applications made in the previous section. Therefore, the LIME technique, which is frequently applied in recent literature as an explainable artificial intelligence method, has been used. The results obtained are as shown in Table 5.

As can be seen in the table, the variables with positive coefficients indicate a positive effect in the target model, while negative values indicate a negative effect.

According to the result obtained by the LIME method, the Current Ratio, Receivables Turnover, and Market Value / Book Value (MV/BV) have a positive effect in the ROA prediction model, while they have a negative effect in the ROE and NPM target models.Liquidity Ratio and Cash Ratio have a positive effect in the ROA, ROE, and NPM models, while inventory turnover has a negative effect in the models.Asset Growth and Price/Earnings (P/E) have a positive effect in the ROA and ROE model, while they have a negative effect in the NPM model. Acounts Payable

Table 5. LIME coefficients regarding the importance levels of input variables

Variable	ROA	Rank	ROE	Rank	NPM	Rank
Current Ratio	0.1418	5	-2.8753	1	-276.11	8
Liquidity Ratio	0.0028	10	0.5606	6	567.8075	2
Cash Ratio	0.0003	12	0.0274	10	9.0215	10
Total Debt Ratio	0.3642	4	-1.2288	3	81.0083	6
Financing Ratio	-0.0234	8	1.6987	2	543.8790	3
Receivables Turnover	0.4593	3	-0.6288	5	-800.9586	7
Inventory Turnover	-0.5714	2	-0.0140	11	-2.8461	11
Accounts Payable Turnover	-0.0021	11	0.1004	7	-1.62e+03	4
Current Asset Turnover	-0.7955	1	0.0983	8	-8.64e+03	1
Asset Growth	0.0224	9	0.0030	12	-22.4878	9
Price/Earnings (P/E)	0.0335	7	1.1512	4	-1.2605	12
Market Value / Book Value (MV/BV)	0.1111	6	-0.0338	9	-89.7799	5

Turnover and Current Asset Turnover have a negative effect in the ROA and NPM model, while they have a positive effect in the ROE model. Total Debt Ratio has a positive effect in the ROA and NPM model, while it has a negative effect in the ROE. Financing Ratio has a negative effect in the ROA model, while it has a positive effect in the ROE and NPM models.

When the values seen in the table are ranked according to absolute degree, the inputs that most affect the ROA target variable are the Current Asset Turnover and Stock Turnover Ratio negatively, while the Receivables Turnover Ratio positively affects it. The least affecting variables are Cash, Debt Turnover, and Liquidity ratios.

For the ROE target variable, the most affecting ratios are Current Ratio (negative), Financing Ratio (positive), and Financial Leverage Ratio (negative). The least affecting variables are Asset Growth, Stock Turnover, and Cash ratios.

In terms of NPM, the most affecting ratios are Current Asset Turnover, Liquidity, and Financing ratios. The least affecting ones are Price/Earnings, Stock Turnover Ratio, and Cash Ratio.

7 Conclusion and suggestions

Energy is a fundamental driver of global changes, influencing economic and socio-cultural transformations in countries. The increasing demand for energy, driven by factors like population growth, industrialization, urbanization, and globalization, has led to a rise in production, trade, and the need for natural resources. This growing demand for energy is further fueled by new technologies that require energy for the production and consumption of goods and services. Ensuring energy supply security and managing energy resources efficiently are crucial for both economic development and environmental sustainability, as the availability of energy resources is closely linked to a country's growth and future prospects.

This study aims to predict the profitability of companies using algorithms and to identify the variables that have a significant impact on profitability. Therefore, a total of 17 algorithms were run separately, and it was observed that the Bagged Tree algorithm produced successful results for the ROA target variable, the Boosted Tree model for the ROE model, and the Linear SVM algorithm for the NPM model. Then, the input variable that most affects the target variable within the model was examined using the LIME algorithm. From an algorithmic perspective, it was found that the available financial ratios could make moderately successful predictions for the ROA and ROE target variables. However, it was observed that the model for the NPM target variable could not make sufficiently successful predictions. In this case, it can be stated that the success of the algorithm depends on the structure of the variables. The results obtained vary significantly according to the target variable. For example, in the model for the ROA variable, the Current Asset Ratio; for the ROE, the Current Ratio; and for the NPM, the Current Asset Turnover Rate are highlighted as the most important variables.

In the literature, it is observed that similar studies are examined using panel regression analysis [79, 80]. Although machine learning algorithms can be applied to panel data, certain characteristics specific to panel data, such as fixed effects and autocorrelation, may be overlooked in standard machine learning models due to their algorithmic approach. However, machine learning techniques can play a complementary role in reducing the dimensionality of panel data, discovering patterns, or enhancing prediction accuracy. This study aims to implement machine learning techniques and, in particular, the increasingly prominent XAI (Explainable Artificial Intelligence) methodology. In future studies, new algorithms integrating panel data, machine learning, and explainable artificial intelligence models could be developed and applied.

This study has examined the determinants of financial performance in energy sector firms, with the most appropriate model selected through machine learning methods. The findings show that financial ratios play a significant role in determining the financial performance of energy companies. Additionally, with the growth of Türkiye's energy sector and the anticipated increase in future energy demand, it is clear that competition within the sector is intensifying, and that companies with strong financial performance are crucial for ensuring the sector's sustainability. In this context, developing an effective strategy to improve the financial performance of energy companies is of great importance for both sectoral development and economic growth. This study aims to provide valuable insights for investors and policymakers in the energy sector, helping them understand how developments in the sector are related to financial outcomes.

These findings offer several contributions in terms of impacts at the energy sector, academic literature, and policy level. In particular, the impact of the results obtained with the LIME method on the decision-making processes of energy companies has various meanings at sectoral, academic and policy levels.

The findings reveal that various ratios used in the financial analysis of energy companies have different effects on their performance. For example, Total Debt Ratio and Receivables Turnover rates have a positive effect on Return on Assets (ROA), while Inventory Turnover and Current Asset Turnover rates have a negative effect. Such information is important for financial decision-makers in the energy sector. Especially in the period when financial performance is evaluated, understanding which ratios have the most impact can help companies use their resources more efficiently and achieve strategic goals. By taking these key indicators into account to improve their financial performance, energy companies can improve their operational efficiency, optimize debt management, and improve their liquidity situation.

In the academic literature, it seems that more research needs to be done on machine learning methods and especially how LIME techniques can be used in financial analysis. Unlike traditional financial analysis methods, LIME's ability to clarify the insight of the model and determine the importance of the variables provides a valuable method for future academic studies. Furthermore, these findings will provide a more detailed understanding of the factors that affect financial performance and increase the explainability of financial analysis models. This will allow decision support systems in particular to become more reliable and transparent.

From the point of view of policymakers and regulators, such results can be useful for developing a more effective supervisory and regulatory strategy in the energy sector. For example, policymakers make adjustments to the sector by taking into account ratios that have a negative or positive impact on financial performance in the energy sector and can enable companies to achieve a more sustainable growth model. In addition, the positive impact of ratios such as the Financing Ratio on ROE and NPM can be useful in developing recommendations for financial management policies.

Investors and governments can consider such financial metrics and provide appropriate incentives to spur growth in the industry.
In summary, these results can influence the way companies in the energy sector conduct financial analysis, contribute to academic studies, and provide valuable insights for regulators shaping energy policies.

Declarations

Use of AI tools

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

Data availability statement

No Data associated with the manuscript.

Ethical approval (optional)

The authors state that this research complies with ethical standards. This research does not involve either human participants or animals.

Consent for publication

Not applicable

Conflicts of interest

The authors declare that they have no conflict of interest.

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Author's contributions

H.H.Y.: Conceptualization, Investigation, Data Curation, Writing - Review & Editing, Supervision. O.F.R.: Methodology, Validation, Data Curation, Software, Visualization, Writing - Review & Editing. C.Y.Y.: Data Curation, Writing - Review & Editing, Supervision. All authors have read and agreed to the published version of the manuscript.

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