Ekonomi, Politika & Finans Araştırmaları Dergisi, 2025, 10(1): 160-183
Journal of Research in Economics, Politics & Finance, 2025, 10(1): 160-183
Araştırma Makalesi / Research Article, https://doi.org/10.30784/epfad.1602204

THE COMPARISON OF ARTIFICIAL NEURAL NETWORKS AND PANEL DATA ANALYSIS ON PROFITABILITY PREDICTION: THE CASE OF REAL ESTATE INVESTMENT TRUSTS[*]

Kârlılık Tahmininde Yapay Sinir Ağları ve Panel Veri Analizinin Karşılaştırılması: Gayrimenkul Yatırım Ortaklıkları Örneği

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Keywords:
Profitability Prediction,
Artificial Neural Network,
Panel Data

JEL Codes:
G17, C33, C45

Abstract

In recent years, machine learning techniques have come to the forefront for profitability forecasting due to their flexibility in computation, ability to work with large and diverse data types, and capability to predict real-time changes. In addition, predicting profitability in practice is challenging and requires expertise. The primary aim of this study is to determine the most suitable profitability prediction model using Artificial Neural Network (ANN) algorithms, one of the machine learning techniques. Furthermore, the ANN prediction model was applied to the data set for the 2010-2019 quarters created from the financial statements of Real Estate Investment Trusts (REITs) companies traded in Borsa Istanbul (BIST) and the prediction success of the ANN technique was interpreted by comparing the findings obtained with the findings obtained as a result of panel data analysis. The comparison of these values with the findings of the panel data analysis has led to the conclusion that ANN prediction models can make more successful forecasts than panel data analysis models.

Anahtar Kelimeler:
Kârlılık Tahmini,
Yapay Sinir Ağı,
Panel Veri

JEL Kodları:
G17, C33, C45

Öz

Son yıllarda makine öğrenmesi teknikleri, hesaplamadaki esneklikleri, büyük ve çeşitli veri türleriyle çalışabilmeleri ve gerçek zamanlı değişiklikleri tahmin edebilme yetenekleri nedeniyle kârlılık tahmininde ön plana çıkmıştır. Ayrıca uygulamada kârlılığı tahmin etmek zordur ve uzmanlık gerektirir. Bu çalışmanın temel amacı, makine öğrenmesi tekniklerinden biri olan Yapay Sinir Ağları (YSA) algoritmalarını kullanarak en uygun kârlılık tahmin modelini belirlemektir. Ayrıca Borsa İstanbul'da (BİST) işlem gören Gayrimenkul Yatırım Ortaklıkları (GYO) firmalarının mali tablolarından oluşturulan 2010-2019 çeyrek dönemlerine ait veri setine YSA tahmin modeli uygulanmış ve elde edilen bulgular, panel veri analizi uygulanması sonucu elde edilen bulgularla karşılaştırılarak YSA tekniğinin tahmin başarısı yorumlanmıştır. Bu değerlerin yapılan panel veri analizi bulgularıyla karşılaştırılması neticesinde, YSA tahmin modellerinin, panel veri analiz modellerine göre daha başarılı tahmin yapabildiği sonucuna ulaşılmıştır.

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[*] This study has been derived from Ayşegül Peker's doctoral thesis titled "Profitability Estimation with Artificial Neural Networks and Comparison with Panel Data Analysis: The Case of Real Estate Investment Trusts."

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Received Date (Makale Geliş Tarihi): 16.12.2024 *Accepted Date (Makale Kabul Tarihi): 28.02.2025*

1. Introduction

Machine learning techniques have been actively used to analyze financial markets in recent years due to the improvement in computational capability, information processing capability, and ease of access to data. There have been various attempts to make predictions about financial market data, ranging from the traditional time series approach to artificial intelligence (Min, 2020). The ANN is one of the most widely used methods of artificial intelligence, emerged by imitating the human brain (Eğrioğlu et al., 2019).

ANNs are computer-assisted systems used to generate, recognize, predict, and analyze new information using the ability to learn the qualities of the human brain (Yavuz and Deveci, 2012). Due to their generalization, non-linearity, parallelism, flexibility, missing data, fault tolerance, and ability to work with many variables and parameters, ANNs are very successful in providing adaptive solutions based on learning in the analysis of problems that cannot be solved using traditional modeling methods (simple regression models, large-scale structural macro-econometric scale models, Box-Jenkins (ARMA) model and VAR (Vector Autoregressive) modeling techniques, etc.) (Sönmez et al., 2015). A further advantage is that it does not require assumptions about data distribution and variables (Yavuz and Deveci, 2012).

ANNs have been developed as a better alternative to traditional and parametric methods with their nonlinear properties. As machine learning has found a space in every field today, many techniques have developed along with it. One of the fields benefiting the most from these techniques is the finance sector. The integration of ANNs into financial applications emerged in the late 1980s and early 1990s. These applications generally focused on stock prediction or financial earnings forecasting (Schöneburg, 1990; Callen et al., 1996). Although the use of traditional econometric modeling techniques has increased due to the increasing competition in financial markets with the development of technology, they have become insufficient over time. Therefore, ANNs, a more advanced technique, can be used to replace or supplement existing traditional modeling techniques. With the turn of the 2000s, studies advanced with larger datasets and financial indicators, comparing ANN models with traditional models such as logistic regression, multiple regression, and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) (Fernandez-Rodriguez et al., 2000; Olson and Mossman, 2003; Bakar and Tahir, 2009). After 2010, the use of advanced methods, such as deep learning techniques and hybrid models, became more widespread (Saberi et al., 2016; Lado-Sestayo and Vivel-Bua, 2020; Alaameri and Faihan, 2022; Vukovic et al., 2023). When the conducted studies are evaluated, it is generally observed that ANN tends to provide higher performance compared to traditional methods. ANN, in particular, demonstrates superiority in handling the complexity of financial data due to its ability to better model nonlinear relationships (Heo et al., 2020; Ho et al., 2020). However, there are instances where traditional methods, such as multiple regression, have yielded better results in certain studies (Mohamad et al., 2013).

The application of ANNs in different financial areas such as stock performance, financial time series prediction, bankruptcy prediction, bond rating improvement, credit risk analysis, and investment management prediction has yielded very successful results (Burrell and Folarin, 1997). This article aims to predict the regression model for profitability using financial ratios with ANN, one of the machine learning techniques, and to compare it with the results of panel data analysis.

A review of the literature reveals that a significant portion of studies employing ANN focus on predicting bank profitability and stock prices (Desai and Bharati, 1998; Sönmez et al., 2015; Ömürbek et al., 2019; Marak et al., 2022). Considering the more limited datasets available in studies conducted in Turkey, it can be said that research predominantly focuses on the banking sector. This sector is followed by the industrial and manufacturing sectors, REITs, and the technology sector, respectively. In terms of initial public offerings (IPOs), the energy and natural resources sector ranks first, followed by REITs. In recent years, REITs in Turkey have been among the most invested sectors in developing countries like ours. The primary reason for this is that real estate is a traditional investment instrument and generally provides protection against inflation. The value of real estate properties and rental income tend to increase in parallel with inflation rates. REITs typically distribute rental income and capital gains as dividends, ensuring a stable cash flow, particularly in the long term. From this perspective, compared to other sectors, REITs offer more predictable and reliable investment models. Furthermore, for small investors, REITs provide the opportunity to participate in individual capital, large-scale investments, and long-term property ownership. Despite the global increase in studies analyzing the profitability of REIT firms, it is evident that research in this area in Turkey is relatively new, beginning to gain prevalence only in the 2000s (Çelik and Arslanlı, 2020; Aktaş and Darwish, 2020; Tekin, 2021; Coşkuner et al., 2024).

The aim of this study is to estimate a regression model for profitability using ANN, one of the machine learning techniques, based on financial ratios, and to compare the results with panel data analysis. The scope of the application includes REITs listed on BIST and registered with the Capital Markets Board (CMB), which hold a significant market share. REITs are obligated to regularly distribute dividends to fund owners, making them more predictable and reliable compared to other sectors. Additionally, rental income and asset appreciation from REIT investments provide a long-term and balanced investment instrument. Their operation through physical real estate investments also makes them less susceptible to speculative movements in financial markets. Furthermore, REITs are significant as they offer investors the opportunity to invest without requiring substantial capital. In the literature, almost all studies conducted on REIT firms focus on identifying the factors affecting profitability. The motivation for this study arises from the significant role that REITs play in real estate-rich countries like Turkey and the absence of studies that predict the profitability of these firms using ANN models. In this respect, the contribution of the study to the literature is considered significant. Furthermore, the study compares ANN models with panel data analysis models. The lack of research that compares these two models for profitability analysis further highlights the contribution this study will make to the existing literature.

2. Literature Review

It has been observed that studies comparing ANN and panel data analysis methods are limited both globally and in Turkey. Brief mentions and explanations of studies comparing these two methods are provided below. Heo et al. (2020) conducted a comparison using panel data analysis and ANN models to develop alternative methods for explaining and predicting household financial ratios. They found that ANN models provided a better overall model fit when defining and forecasting financial ratios. Similarly, Ho et al. (2020) analyzed the shifting apparel import patterns of the United States (USA) from China and 14 Belt and Road (B&R) countries in Asia.

They applied panel regression models and ANN analyses to data from 1998 to 2018, using their developed model to predict the trade patterns for 2019. Their results demonstrated that the predictive power of the ANN model was superior. Kıral and Çelik (2020) utilized a panel data regression model to identify factors affecting housing prices in Turkey. They then applied an ANN analysis to forecast housing prices based on the identified factors. Their findings indicated that the factors determined by the two methods were inconsistent. Similarly, Parlakkaya et al. (2022) examined the factors influencing the capital structures of conventional and participation banks in the Turkish banking sector. Using financial data from banks between 2010 and 2020, they analyzed the data using both panel data regression and ANN models. The limited studies combining ANN and panel data analysis have contributed to shaping one of the main ideas for our research.

Although REITs in Turkey began operating in the mid-1980s, academic studies on the subject became widespread in the 2000s. Studies specifically focusing on profitability analyses of REITs in both Turkey and the world emerged more prominently toward the late 2010s. A review of the existing literature reveals that various methods have been used to measure REIT profitability. Jakpar et al. (2018) analyzed the factors determining the return on equity (ROE) of eight REITs in Malaysia between 2008 and 2015 using panel data analysis. Similarly, Ocakdan (2019) examined the profitability of 33 REITs in Turkey during the period 2014–2018. His study focused on the annual variations in profitability ratios and analyzed the impact of tax and interest burdens on profitability. Çelik and Arslanlı (2020) aimed to identify the financial ratios affecting asset profitability and market value in REIT firms. Using panel data analysis, they found significant negative relationships between long-term debt-to-total assets, ROE, current ratio, and market value, as well as a significant positive relationship between total assets and market value. Furthermore, positive significant relationships were observed between stock returns, current ratio, ROE, and asset profitability. In their study, Aktaş and Darwish (2020) analyzed financial statement ratios influencing the asset and equity profitability of 32 REITs operating in Turkey. Using panel data analysis on annual data from 2014–2019, they concluded that long-term debt ratios negatively impacted both asset and equity profitability, while other independent variables had no significant effects. Tekin (2021) investigated the factors influencing asset and equity profitability of 21 REITs in Turkey using quarterly data from 2010 to 2019 and applied panel data analysis. Öndeş and Barakalı (2023) examined the effect of interest rate changes on profitability in the real estate sector, utilizing quarterly data from 2011 to 2021. Their findings revealed that commercial and residential interest rates influenced asset profitability. Cunha et al. (2023) explored whether equity profitability in non-publicly traded REITs was affected by housing price increases and GDP data. Analyzing 10 years of data from Portuguese REITs, they used the Canonical Cointegration Regression (CCR) technique for panel data analysis and concluded that housing price increases did not influence equity profitability. Lastly, Coşkuner et al. (2024) compared the factors affecting the profitability of REITs in Turkey and Malaysia. Their study focused on asset and equity profitability as dependent variables and employed a random forest regression method to determine the significance of influencing factors. The results indicated that the most impactful variables for both countries' REITs were the total debt-to-total assets ratio and the logarithm of total assets.

Various analytical methods have been used to measure profitability, yet studies focusing on profitability analyses of REIT firms remain limited. Specifically, it can be clearly stated that profitability forecasting for REIT firms in Turkey using the ANN analysis model has not been conducted previously. From this perspective, employing ANN analysis for profitability forecasting is another factor that has contributed to the formation of the core idea of our study and has helped shape its framework.

3. Methods

3.1. Artificial Neural Networks

An ANN is a system that imitates the information-processing components of a biological nerve cell and is developed accordingly. A neuron is the basic information processing unit in a neural network system. This basic information processing is called a *perceptron*. As in a basic biological neuron structure, the neural cell receives inputs, combines them, processes them, and performs a generally non-linear process. The processed information then results in the final output (Anderson and McNeill, 1992). The structure of an artificial neural cell is shown in Figure 1 (Csáji, 2001):

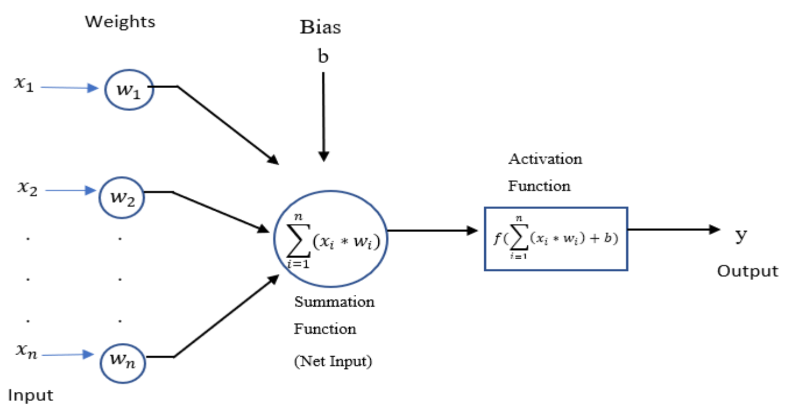


Figure 1. Structure of Artificial Neural Cell

As in a biological neural network, there are sections in an ANN. In ANNs, these sections are called process elements. There are 5 basic sections in each process element. These sections are (Öztemel, 2020):

Stage 1. The input layer is the signals or samples coming from the external environment and representing the values assumed by the variables (Silva et al., 2017).

Stage 2. Weights are adaptive coefficients within the network structure to determine the intensity of the input data recorded by the artificial neural cell (Anderson and McNeill, 1992).

Stage 3. The summation function is the function that calculates the net input to the nerve cell (Öztemel, 2020). The calculated Net Input value is summed with the bias threshold value and passed through the activation function. The bias value is a constant added to the inputs and weights. It is used to adjust the activation function that affects the neuron's output (Alaloul and Qureshi, 2020). The net input formula is as follows.

$$Net\ Input = \sum_{i=1}^{n}(x_i * w_i) + b \quad (1)$$

Stage 4. The activation function is a mathematical function that takes the value obtained from the summation function as input and then converts the value processed in the processing unit of the neural network into the final output (Alaloul and Qureshi, 2020).

Stage 5. The output layer is the final value processed and produced by the nerve cell (Silva et al., 2017).

ANNs consist of 3 parallel layers input layer, hidden layer, and output layer. ANNs are considered in two types of structures layer and multilayer. They can also be classified as feed-forward (non-recurrent) and feed-back (recurrent). While the feedback structure is known as recurrent or auto-relational, the feed-forward structure is known as non-recurrent or non-relational. (Sharma et al., 2012).

In single-layer networks, there is only one input and one output layer. Information flow is always unidirectional from the input layer to the output layer (Silva et al., 2017). In the multilayer network model, each layer consists of units that directly receive their information and send it to the next layer. It consists of an input layer, one or more hidden layers, and an output layer (Kröse and Smagt, 1996).

Single-layer network models are given in Figure 2 and multilayer network models are given in Figure 3 (Silva et al., 2017);

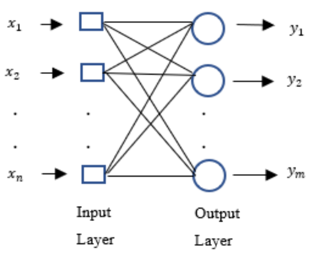


Figure 2. Single Layer Network

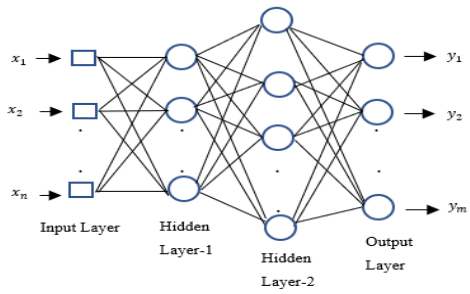


Figure 3. Multilayer Network

According to the direction of data flow, ANNs are classified as feed-forward and feed-back. Feed-forward neural networks are widely used systems with the most powerful structure for nonlinear regression models (Shanmuganathan, 2016). Neural network architecture with a strong structure extending from input units to output units, where neurons are grouped in layers, data flow is provided only by forward connections, but there is no feedback (Kröse and Smagt, 1996). Feedback ANNs are the most widely used method for training the model. The main difference compared to the feed-forward network is that the targeted and obtained output values are propagated back to the layers and the weights are adjusted again (Kukreja et al., 2016).

3.2. Performance Measurements

Various models are compared to assess the prediction accuracy. The best performance metric compatible with these models is selected. Therefore, there are many metrics used to measure performance. Each of these metrics is a function of the actual and predicted values of the time series (Khalil, 2022).

Mean Square Error (MSE), Mean Square Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) are the most commonly used performance measures in time series analysis (Monteiro and Costa, 2018). Although many model performance measures have been used to assess model performance, there is no consensus on the most appropriate metric for model errors (Chai and Draxler, 2014).

Mean Squared Error (MSE) is a measure of the mean squared deviation of predicted values. The mathematical representation of MSE is given below (Adhikari and Agrawal, 2013).

$$MSE = \frac{1}{n}\sum_{t=1}^{n} E_t^2 \tag{2}$$

Mean Absolute Error (MAE) measures the mean absolute deviation of the predicted values from the original values. The mathematical representation of MAE is given below (Adhikari and Agrawal, 2013).

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |E_t| \tag{3}$$

Root Mean Squared Error (RMSE) measures are calculated by taking the square root of the MSE metric. All the properties of MSE also apply to RMSE. (Adhikari and Agrawal, 2013).

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} E_t^2} \tag{4}$$

Determination Coefficient (R^2) is the linear correlation between observations and values corresponding to model predictions (Monteiro and Costa, 2018).

$$R^2 = 1 - \frac{\sum_i^n (y_i - \hat{y}_i)^2}{\sum_i^n (y_i - \bar{y}_i)^2} \tag{5}$$

The determination coefficient shows the explanatory power of dependent variables for independent variables.

3.3. Panel Data Analysis

The term panel or longitudinal refers to a data set allowing the observation of more than one individual, country, firm, or unit over a while (Hsiao, 2014). Panel data consists of N number of units and T number of observations corresponding to these units (Tatoğlu, 2021). Panel data regression is different from normal time series or cross-section regression. The panel data regression model is constructed as follows (Baltagi, 2005).

$$y_{it} = \alpha + \beta X'_{it} + u_{it} \qquad i=1,\ldots\ldots,N;\ t=1,\ldots\ldots,T \tag{6}$$

According to this equation, the following are defined; y_{it}; dependent variable, i; households, individuals, companies, countries, etc. (cross-sectional unit), t; time (time series), α; a fixed unit of measurement, β; slope coefficient of variables, X'_{it}; explanatory variables for i'th observations at time t, u_{it}; error component.

Error component is expressed;

$$u_{it} = \mu_i + v_{it} \tag{7}$$

μ_i; unobservable individual-specific effect, v_{it}; intrinsic error (residual error term)

In panel data analysis, the most appropriate method should be determined according to the condition and characteristics of the data. For this reason, homogeneity, horizontal cross-section dependence, and unit root tests should be performed. The most appropriate model is determined according to the results obtained. The model applied in this study is based on the Panel OLS technique. Panel OLS consists of pooled least squares, fixed, and random effects models. At this stage, it is important to choose one of the appropriate models. In the present study, the appropriate model was determined as the fixed effects model.

The Fixed Effects Model (FEM) is widely used when neglected variables that are constant over time and differ across units, called unobservable heterogeneity (individual-specific effect-μ_i) or fixed effects, are to be controlled.

The fixed effects model regression equation is defined as follows (Baltagi, 2005).

$$y_{it} = \alpha + \beta x_{it} + \mu_i + v_{it} \tag{8}$$

In case of averaging over time;

$$\bar{y}_i = \alpha + \beta \bar{x}_i + \mu_i + \bar{v}_i \tag{9}$$

equation 8 is then subtracted from equation 9.

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + (v_{it} - \bar{v}_i) \tag{10}$$

4. Estimation Results and Comments

The financial statement data of REITs traded on the BIST for the quarterly periods of 2010-2019 are used to predict profitability. Due to the 2008 economic crisis and its impact in 2009, the pandemic in 2020, and the extremely rapid increase in housing prices in the following years, the analysis scope period was determined as the quarter periods of 2010-2019 to obtain healthier data. Data were obtained from the Finnet Financial Analysis program, the Public Disclosure Platform ("PDP"), the Turkish Statistical Institute ("TSI"), and the Central Bank of the Republic of Turkey ("CBRT") official websites. As some of the 48 companies traded on the BIST have recently started their operations and a few companies did not have complete data within the period of the analysis, the data of 27 companies were analyzed. The companies included in the analysis are given in Table 1.

Table 1. REIT Companies in the Scope of Analysis

BIST Index Code	REIT Companies
AKFGY	Akfen Real Estate Investment Trust Inc.
AKSGY	Akiş Real Estate Investment Trust Inc.
AKMGY	Akmerkez Real Estate Investment Trust Inc.
ALGYO	Alarko Real Estate Investment Trust Inc.
ATAGY	Ata Real Estate Investment Trust Inc.
AGYO	Atakule Real Estate Investment Trust Inc.
AVGYO	Avrasya Real Estate Investment Trust Inc.
DZGYO	Deniz Real Estate Investment Trust Inc.
DGGYO	Doğuş Real Estate Investment Trust Inc.
EKGYO	Emlak Konut Real Estate Investment Trust Inc.
HLGYO	Halk Real Estate Investment Trust Inc.
IDGYO	İdealist Real Estate Investment Trust Inc.
ISGYO	İş Real Estate Investment Trust Inc.
KLGYO	Kiler Real Estate Investment Trust Inc.
KGYO	Koray Real Estate Investment Trust Inc.
MRGYO	Marti Real Estate Investment Trust Inc.
NUGYO	Nurol Real Estate Investment Trust Inc.
OZKGY	Özak Real Estate Investment Trust Inc.
OZGYO	Özderici Real Estate Investment Trust Inc.
PEGYO	Pera Real Estate Investment Trust Inc.
RYGYO	Reysaş Real Estate Investment Trust Inc.
SRVGY	Servet Real Estate Investment Trust Inc.
SNGYO	Sinpaş Real Estate Investment Trust Inc.
TRGYO	Torunlar Real Estate Investment Trust Inc.
TSGYO	Tskb Real Estate Investment Trust Inc.
VKGYO	Vakif Real Estate Investment Trust Inc.
YGYO	Yeşil Real Estate Investment Trust Inc.

Considering the studies on the measurement of profitability and performance of REITs, the variables to be evaluated within the scope of the analysis are given in Table 2. According to Table 2, 2 dependent variables and 25 independent variables were determined. Using the determined ratios and various variables and parameters, return on assets and ROE was tried to be estimated.

Table 2. Variables Used in the Analysis

Dependent Variables			
Profitability Ratios	B1	Return on Assets	Net Profit/Total Assets
	B2	Return on Equity	Net Profit / Total Equity
Independent Variables			
Liquidity Ratios	L1	Current Ratio	Current Assets/Short-Term Liabilities
	L2	Acid-Test Ratio	(Current Assets-Stocks)/Short Term Liabilities
	L3	Cash Rate	(Cash and Cash Equivalents + Marketable Securities)/Short Term Liabilities
Financial Structure Ratios	F1	Debt to Equity Ratio	Total Debt/Total Resources
	F2	Debt/Equity Ratio	Total Debt/Total Equity
	F3	Equity Ratio	Equity/Total Assets
	F4	Short Term Debt Ratio	Short-Term Debt/Total Resources
	F5	Long-Term Debt Ratio	Long-Term Debt/Total Resources
	F6	Currency Risk	(Absolute(Foreign Currency Assets - Foreign Currency Liabilities))/ Total Equity
	F7	Equity Multiplier	Total Assets/Total Equity

Table 2. Continue

Activity Ratios	E1	Receivables Turnover Rate	Net Sales/Average Trade Receivables
	E2	Net Working Capital Turnover	Net Sales/Average Net Working Capital
	E3	Asset Turnover	Net Sales/Average Assets
	E4	Equity Turnover Rate	Net Sales/Average Shareholders' Equity
Market Performance Ratios	P1	Price/Earnings Ratio	Market Capitalization/Net Profit
	P2	Market Value/Book Value (PD/BV) Ratio	Market Capitalization/ Equity
	P3	Rate of Return per Share	Net Profit/Number of Shares in Circulation
	P4	Tobin's Q Ratio	(MarketValue+(Short-Term Assets-Short-Term Assets)+Uvb)/Total Assets
Competition and Size Ratios	R1	Enterprise Size-1	Log(Total Assets)
	R2	Enterprise Size-2	Log(Total Net Sales)
	R3	Market Share	Net Sales of the Enterprise/Total Net Sales of the Enterprises in the Sector
Makro Variables	M1	Inflation	Percentage Change in CPI Compared to the Previous Period
	M2	Economic Growth Rate (GDP)	Percentage Change in GDP Compared to the Previous Period
	M3	Current Account Deficit Ratio	Current Account Balance/GDP
	M4	Interest Rate	Interest Rate Applied to Deposits

To ensure that the Panel Data Analysis and ANN models provide better results and to identify the effective variables, the Factor Analysis Principal Components method was applied. With this method, the number of variables previously identified was reduced. Table 3 shows the rotated components matrix obtained as a result of factor analysis. As a result of the factor analysis, 6 factors with an eigenvalue above 1 were taken into consideration. A total of 17 independent variables grouped under these factors were obtained. The KMO (Kaiser Meyer Olkin) was found to be 0.675 in the analysis and it was determined that the distribution was sufficient for factor analysis.

Table 3. Rotated Components Matrix

Variables	1	2	3	4	5	6
L2-Acid-Test	0.963					
L3-Cash Rate	0.960					
L1-Current Ratio	0.786					
M3- Current Deficit Ratio		0.936				
M2- Economic Growth Rate (GDP)		-0.875				
M4- Interest Rate		0.870				
E4- Equity Turnover Rate			0.963			
E3- Active Speed			0.962			
E2- Net Work. Cap. Turnover Rate			0.728			
R1- Business Size1				0.805		
R2- Business Size2				0.797		
R3- Market Share				0.767		
F7- Equity Multiplier					0.757	
F5- UVB Ratio					0.685	
F3- Equity Ratio					-0.656	
P3- Return Per Share						0.749
P4- Tobin's Q Ratio						0.696

In line with the factor analysis, since F1, F2, and F3 variables have similar characteristics in terms of measuring capital accumulation and borrowing, only the F3 variable was used in the analysis. In terms of the scope of the F3 variable, it indirectly shows the sustainability of debts compared to the F1 and F2 variables. The F4 variable was excluded from the scope of the analysis since it decreased the KMO (Kaiser Meyer Olkin) and total explained variance values. F6, E1, and P2 variables were grouped under other factors, while P1 and M1 variables were not included in the analysis since they were below 0.50 factor loadings. As a result, 2 dependent and 17 independent variables were obtained to be used in Panel Data Analysis and ANN models. After determining the variables obtained for profitability prediction, panel data analysis was first applied to the data.

Homogeneity and inter-unit correlation tests were applied to the data to select the most appropriate model for panel data analysis. It was found that the ratios affecting the B1 return on assets variable are heterogeneous, while the ratios affecting the B2 ROE variable are homogeneous.

Based on the results of the Breusch-Pagan (LM- Lagrange Multiplier) Test, Pesaran LM CD Test, and Friedman Test, the null hypothesis is rejected at $p<0.05$ significance level for return on assets and ROE dependent variables. Therefore, it is concluded that there is an inter-unit correlation. Since inter-unit correlation is detected, 2nd generation unit root tests should be applied. Among the 2nd generation unit root tests, the most appropriate test for both homogeneity and heterogeneity is Pesaran's (2007) CIPS test (Pesaran, 2007). According to Table 4, since CIPS>Critical Value in absolute value at $p<0.05$ significance level, hypothesis H_0 is rejected. It is concluded that all variables are stationary at the level.

Table 4. CIPS Unit Root Test Results Table

Variables	CIPS Value	5% Critical Value	Level
B1- Return on Assets	-3.969	-2.16	I(0)
B2 - Return on Equity	-4.887	-2.16	I(0)
L1-Current Ratio	-3.809	-2.16	I(0)
L2-Acid-Test Ratio	-3.554	2.16	I(0)
L3-Cash Rate	-3.760	-2.16	I(0)
F3-Equity Ratio	-2.591	-2.16	I(0)
F5-UVB Ratio	-2.297	-2.16	I(0)
F7-Equity Multiplier	-2.863	-2.16	I(0)
E2-Net Work. Cap. Turnover	-4.452	-2.16	I(0)
E3-Asset Turnover	-4.813	-2.16	I(0)
E4-Equity Turnover Rate	-4.127	-2.16	I(0)
P3-Return Per Share	-3.947	-2.16	I(0)
P4-Tobin's Q Ratio	-2.346	-2.16	I(0)
R1-Business Size-1	-2.863	-2.16	I(0)
R2-Business Size-2	-3.472	-2.16	I(0)
R3-Market Share	-4.795	-2.16	I(0)
M2-GDP Ratio	-5.807	-2.16	I(0)
M3-Current Deficit Ratio	-5.782	-2.16	I(0)
M4-Interest Rate	-6.137	-2.16	I(0)

Note: *$*p<0.05$*

Since all variables are stationary at a level as a result of the unit root test, the Panel OLS (Ordinary Least Squares) test should be applied. Panel OLS consists of pooled least squares, fixed, and random effects models. The important thing here is to choose one of these models. For model selection, the results of the F test, LM (Breusch-Pagan) test, and Hausman test should be taken into consideration.

According to the test results, since the probability values of the F test, LM test, ALM (Adjusted Lagrange Multiplier) test, and Hausman test for the return on assets variable are below the $p<0.01$ significance level, hypothesis H_0 is rejected. The F test gives the fixed effects model and the LM/ALM test gives the random effects model. The Hausman test applied to choose between the two models resulted in the fixed effects model. For the ROE variable, the F test gives the fixed effects model and the LM/ALM test gives the pooled least squares model. The Hausman test applied to choose between the two models resulted in the fixed effects model.

Changing variance and autocorrelation tests should be applied to analyze the data correctly. Autocorrelation is tested by Durbin-Watson and Baltagi-Wu LBI (Locally Best Invariant) and variance is tested by Modified Wald Test.

Table 5. B1-Active Profitability Driscoll-Kraay Robust Fixed Effects Model Estimation Results

B1- Return on Assets	**Coefficients**	**Driscoll-Kraay Resistive Standard Error**	**t**	**P>t**	**[95%Conf.**
L1-Current Ratio	0.003	0.002	1.840	0.077	-0.000
L2-Acid-Test Ratio	0.029	0.058	0.510	0.616	-0.089
L3-Cash Rate	-0.041	0.056	-0.720	0.475	-0.156
F3-Equity Ratio	6.289	2.097	3.000	0.006**	1.978
F5-UVB Ratio	-1.339	1.703	-0.790	0.439	-4.839
F7-Equity Multiplier	-0.005	0.013	-0.390	0.697	-0.033
E2-Net Wor. Cap.Turnover	-0.006	0.005	-1.210	0.239	-0.015
E3-Asset Turnover	-0.501	0.264	-1.900	0.069	-1.043
E4-Equity Turnover Rate	0.407	0.245	1.660	0.109	-0.097
P3-Return Per Share	8.110	0.526	15.420	0.000**	7.029
P4-Tobin's Q Ratio	-1.120	0.223	-5.030	0.000**	-1.578
R1- Business Growth -1	1.340	0.866	1.550	0.134	-0.439
R2- Business Growth -2	0.135	0.191	0.710	0.484	-0.257
R3-Market Share	0.779	1.848	0.420	0.677	-3.019
M2-Eco.Growth Rate(GDP)	5.603	8.435	0.660	0.512	-11.734
M3-Current Deficit Ratio	15.604	9.222	1.690	0.103	-3.353
M4-Interest Rate	-0.112	0.044	-2.520	0.018**	-0.203
Constant	-13.683	7.313	-1.870	0.073	-28.714
F(17, 26)		133.74	MSE		
Prob > F		0.0000	MAE	0.000001908	
R^2		0.5018	RMSE		
B1- Return on Assets		**Test Statistic**		**p value**	
F Test		7.39		0.000***	
LM/ALM Test		9.84		0.000***	
Hausman Test		84.02		0.000***	
Heteroscedastic Test					
Modified Wald		1990.57		0.000***	
Autocorrelation Test					
Durbin-Watson		1.5429		-	
Baltagi-Wu LBI		1.6007		-	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As a result of the tests applied, the Driscoll-Kraay Estimator, an estimator resistant to the fixed effects model, was applied since there was an inter-unit correlation, changing variance, and autocorrelation problems. According to the return on assets variable, the error performance and coefficient of determination of the findings obtained by applying the Driscoll-Kraay robust fixed effects model are given in Table 5.

According to Table 5, the F statistic of the model was found significant at p<0.01 level. The R^2 value is 0.5018, which indicates that the independent variables can explain 50% of the dependent variable. Among the MSE, MAE, and RMSE error metrics measuring the prediction performance according to the model, the MAE metric gave the minimum error of 0.000001908. The analysis model established according to the return on assets variable is given below.

$$B1 = -13.683 + 6.289 * F3 + 8.110 * P3 + (-1.1120) * P4 + (-0.112) * M4 \tag{11}$$

The variables F3-equity ratio, P3-return per share ratio, P4-Tobin's Q ratio, and M4-interest rate are statistically significant on the return on assets ratio. While the F3-equity ratio and P3-return per share ratio have a positive effect on return on assets, P4-Tobin's Q ratio and M4-interest rate have a negative effect on return on assets. The most influential ratio on return on assets is the earnings per share ratio. This can be explained by the increase in net profit from sales, which consequently enhances return on assets.

According to the ROE variable, the error performance and coefficient of determination of the findings obtained by applying the Driscoll-Kraay robust fixed effects model are given in Table 6. According to the Driscoll-Kraay robust fixed effects model estimation results for the ROE dependent variable, the F statistic of the model was found significant at p<0.05 level. The R^2 value is 0.7335 and this ratio shows that the independent variables can explain 73% of the dependent variable. As in the return on assets variable, the metric that best measures the prediction performance is MAE with a value of 0.00015062. The analysis model for the ROE variable is as follows.

$$\begin{aligned} B2 = 93.026 + (-60.166) * F3 + (-50.108) * F5 + (-2.468) * F7 + 125.522 \\ * E3 + (-117.593) * E4 + 29.527 * P3 + 159.530 * R3 \\ + (-1.275) * M4 \end{aligned} \tag{12}$$

The variables F3-equity ratio, F5-Uvb ratio, F7-equity multiplier, E3-asset turnover ratio, E4-equity turnover ratio, P3-return per share ratio, R3-market share, and M4-interest rate are statistically significant on the ROE ratio. While the F3-equity ratio, F5-long-term borrowing ratio, F7-equity multiple ratio, E4-equity turnover ratio, and M4-interest rate have a negative effect on ROE, E3-asset turnover ratio, P3-return per share ratio and R3-market share ratio have a positive effect on ROE. The fact that the asset turnover ratio has a positive and significant coefficient indicates effective asset management by businesses. Similarly, the positive and high impact of the market share ratio can be explained by the ability to achieve higher product sales within the sector.

Table 6. B2 - Return on Equity Driscoll-Kraay Robust Fixed Effects Model Estimation Results

B2- Return on Assets	Coefficients	Driscoll-Kraay Resistive Standard Error	t	P>t	[95%Conf.
L1-Current Ratio	0.002	0.010	0.240	0.810	-0.018
L2-Acid-Test Ratio	-0.408	0.338	-1.200	0.239	-1.103
L3-Cash Rate	0.367	0.313	1.170	0.251	-0.276
F3-Equity Ratio	-60.166	13.121	-4.590	0.000**	-87.136
F5-UVB Ratio	-50.108	20.534	-2.440	0.022**	-92.316
F7-Equity Multiplier	-2.468	1.011	-2.440	0.022**	-4.547
E2-Net Work. Cap. Turnover	-0.216	0.174	-1.240	0.226	-0.574
E3-Asset Turnover	125.522	37.132	3.380	0.002**	49.197
E4-Equity Turnover Rate	-117.593	34.654	-3.390	0.002**	-188.826
P3-Return Per Share	29.527	7.237	4.080	0.000**	14.650
P4-Tobin’s Q Ratio	-3.690	2.628	-1.400	0.172	-9.092
R1-Business Growth -1	-3.543	11.588	-0.310	0.762	-27.362
R2-Business Growth -2	1.700	0.928	1.830	0.079	-0.208
R3-Market Share	159.530	46.762	3.410	0.002**	63.408
M2-Eco.Growth Rate(GDP)	-87.043	87.231	-1.000	0.328	-266.349
M3-Current Deficit Ratio	-44.736	91.745	-0.490	0.630	-233.321
M4-Interest Rate	-1.275	0.461	-2.760	0.010**	-2.223
Constant	93.026	100.957	0.920	0.365	-114.495
F(17, 26)	42.64		MSE	-	
Prob > F	0.0000		MAE	0.00015062	
R^2	0.7335		RMSE	-	

B2- Return on Assets	Test Statistic	p value
F Test	1.57	0.0348**
LM/ALM Test	0.07	0.4709
Hausman Test	36.22	0.0027***
Heteroscedastic Test		
Modified Wald	1.1e+06	0.000***
Autocorrelation Test		
Durbin-Watson	1.9068	-
Baltagi-Wu LBI	1.9755	-

Note: *** p<0.01, ** p<0.05, * p<0.1

ANN analysis backpropagation MLP (Multi-Layer Perceptron) Regressor model was applied for profitability prediction. For the analysis, modeling was performed with Python 3.8.13 programming language, and libraries with accessible open-source data processing algorithms were used. In this context, the NumPy library was utilized for processing numerical data, while the Pandas library was employed for constructing time-labeled series and structured tables. During the model training phase, the Scikit-Learn (Sklearn) library was used for model development and the evaluation of model performance metrics. For data visualization and graphical representation, the Seaborn library, along with Matplotlib and Plotly, was employed to effectively illustrate the findings. Details about the network information of the ANN models established for B1-Active Profitability and B2- ROE are given in Table 7.

Table 7. ANN Model Network Information

B1- Return on Assets		**B2-Return on Equity**	
Network Arch.	MLP Regressor	Network Arch.	MLP Regressor
Training Type	Supervised Learning	Training Type	Supervised Learning
Function Type	Multilayer	Function Type	Multilayer
Error Metrics	MSE, MAE, RMSE, R^2	Error Metrics	MSE, MAE, RMSE, R^2
No of Hidden. Layers	4	No of Hidden Layers	4
Iteration	1000	Iteration	303
Network Arch.	40-30-20-10	Network Arch.	60-45-25-10
Activation Function	Hiperbolik Tangent (tanh)	Activation Function	Rectified Linear Unit (Relu)
Momentum Coef.	0,9	Momentum Coef.	0,9
Learning Coefficient	0,001	Learning Coefficient	0,001
Scaling	Standard Scaler	Scaling	Standard Scaler

The MLP Regressor model was used for profitability forecasting. After defining the dependent and independent variables, a standardization process was applied to eliminate differences between values while preserving the data structure. Error metrics were identified before model installation. By comparing the determined metrics, the metric that gave the least error was determined. During the model development phase, the standardized data was divided into three sets: training set, validation set, and test set. Specifically, 80% of the data was allocated for training, 10% for validation, and 10% for testing. In defining the ANN architecture, different models were tried by adjusting hyperparameters such as a hidden layer, learning rate, momentum coefficient, and activation function while training the network. At this stage, weights were assigned. The next step is the validation phase, where hyperparameters are adjusted until the network achieves minimum error after training. Finally, in the testing phase, the model's generalization ability was evaluated.

Different forecasting models are tested for return on assets and ROE variables. The performance results of the models are evaluated comparatively with MSE, MAE, and RMSE error metrics and R^2 values that measure model adequacy.

According to Table 8, the MSE metric has the best performance with the minimum error for the B1 return on assets prediction. Among the models, the best R^2 result, which shows the accuracy and explanatory power, is given by Model 4. According to this model, the network architecture has 4 layers and the hidden layers are realized as 40-30-20-10. The training performance of the model was 90% and the validation performance was 87%. It can be said that the model, whose test performance was 85%, achieved success. The overall performance of the model was 87%.

Table 8. B1 Return on Assets Error and Performance Measures Table

	Performance	MSE	MAE	RMSE	R^2
Model: 1 Number of Hidden Layers: 15-3	Test	0.15613	0.28104	0.39514	0.83873
	Training	0.23365	0.29677	0.48338	0.79084
	Verification	0.11332	0.24476	0.33664	0.83677
	General	0.23160	0.29607	0.48124	0.76839
Model: 2 Number of Hidden Layers: 35-20-15	Test	0.20911	0.27854	0.45728	0.83277
	Training	0.17696	0.25907	0.42067	0.83365
	Verification	0.11702	0.24212	0.34208	0.84089
	General	0.17288	0.26226	0.41579	0.82711
Model: 3 Number of Hidden Layers: 30-25-20-10	Test	0.14700	0.24624	0.38341	0.84816
	Training	0.12780	0.22081	0.35749	0.87782
	Verification	0.09078	0.20486	0.30130	0.87657
	General	0.13177	0.22707	0.36301	0.86822
Model: 4 Number of Hidden Layers: 40-30-20-10	Test	0.18206	0.24954	0.42668	0.85139
	Training	0.11081	0.21459	0.33288	0.90080
	Verification	0.12791	0.23220	0.35765	0.87172
	General	0.12316	0.22403	0.35095	0.87683
Model: 5 Number of Hidden Layers: 55-35-28-10	Test	0.14838	0.25016	0.38520	0.84674
	Training	0.16283	0.23883	0.40353	0.84349
	Verification	0.08285	0.20281	0.28784	0.88734
	General	0.15867	0.23644	0.39834	0.84132

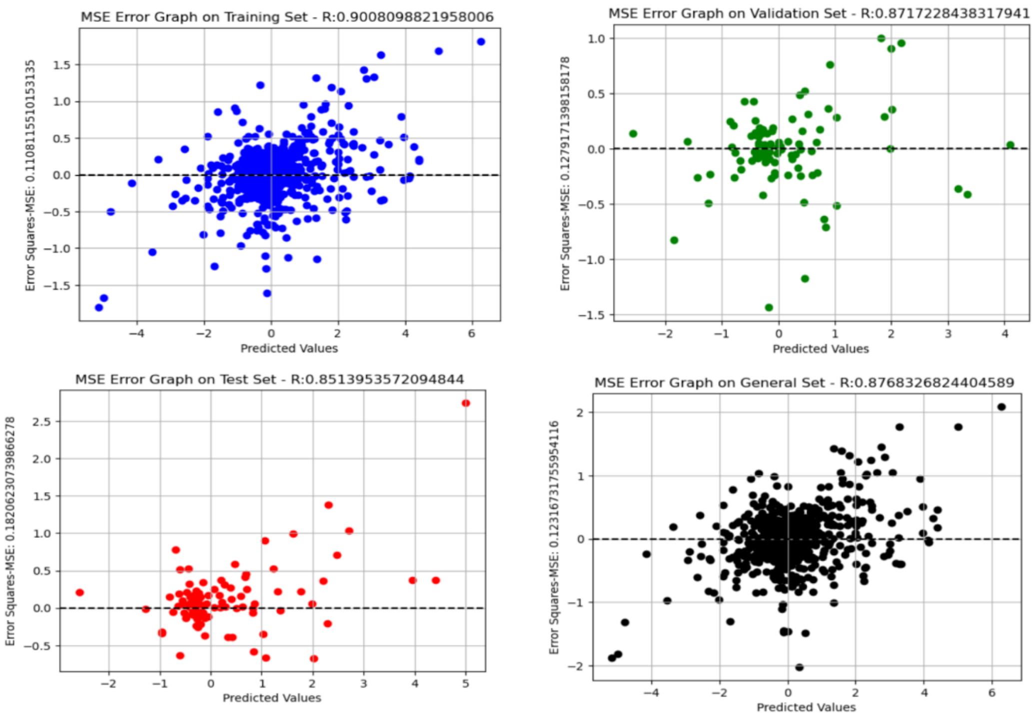
Model error and performance measures for ROE are given in Table 9. According to Table 9, the best performance with the minimum error for the B2 ROE prediction belongs to the MSE metric, just like the return on assets variable. Among the models, the best R^2 result indicating accuracy and explanatory power is given by Model 5. According to this model, the network architecture has 4 layers and the hidden layers are realized as 60-45-25-10. The training performance of the model was 98% and the validation performance was 94%. It can be said that the model, whose test performance was 96%, achieved success. The overall performance of the model was realized as 98%.

Table 9. B2 Return on Equity Error and Performance Measures Table

	Performance	MSE	MAE	RMSE	R^2
Model: 1 Number of Hidden Layers: 25-7	Test	0.06476	0.06669	0.09832	0.94828
	Training	0.01938	0.07422	0.13923	0.98276
	Verification	0.03356	0.09546	0.18319	0.91979
	General	0.02783	0.08169	0.16682	0.97216
Model: 2 Number of Hidden Layers: 15-8-7	Test	0.01202	0.07616	0.10965	0.93567
	Training	0.01616	0.07749	0.12715	0.98316
	Verification	0.01947	0.09748	0.13955	0.93342
	General	0.15168	0.09404	0.38947	0.84831
Model: 3 Number of Hidden Layers: 30-10-3	Test	0.01199	0.06193	0.10951	0.93584
	Training	0.01510	0.06963	0.12291	0.98427
	Verification	0.02621	0.09648	0.16191	0.91037
	General	0.02068	0.07091	0.14383	0.97931
Model: 4 Number of Hidden Layers: 40-35-20-10	Test	0.01451	0.07826	0.12047	0.92236
	Training	0.01753	0.08693	0.13242	0.98440
	Verification	0.02716	0.10350	0.16480	0.90715
	General	0.01931	0.07533	0.13897	0.98068
Model: 5 Number of Hidden Layers: 60-45-25-10	Test	0.01200	0.07602	0.10956	0.96415
	Training	0.01613	0.07163	0.12701	0.98664
	Verification	0.02211	0.08204	0.14872	0.94714
	General	0.01824	0.07396	0.13509	0.98175

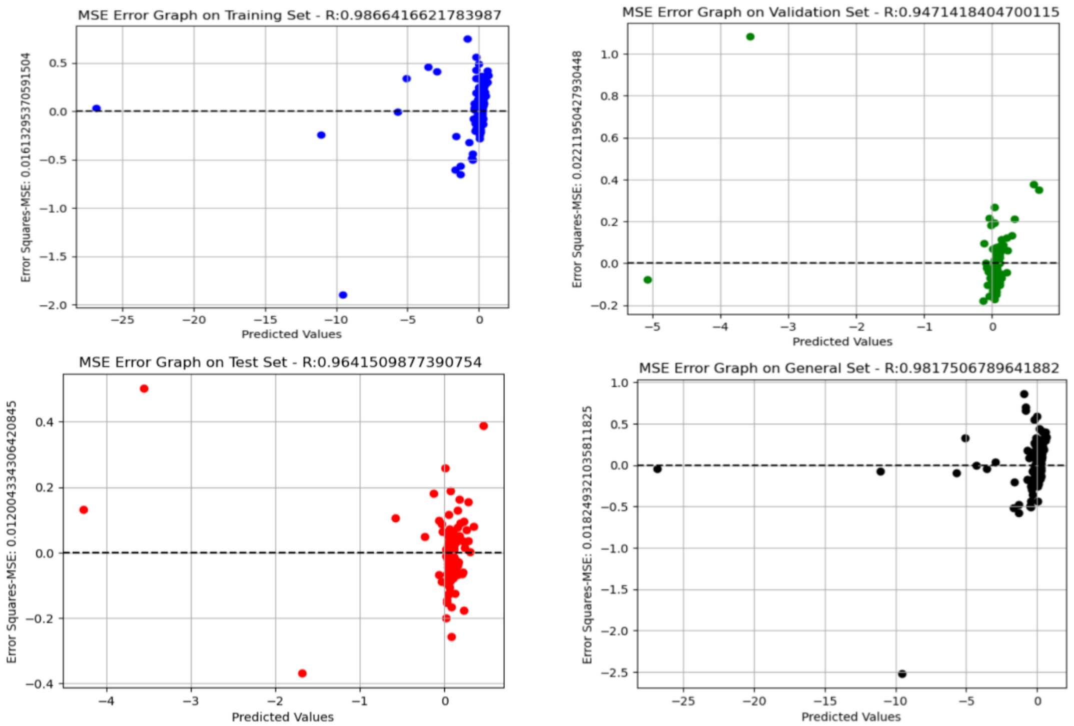
It is concluded that the metric with the least error for the dependent variables, return on assets and ROE, is MSE. The training, validation, test set, and overall performance error distributions for these variables are given in Graphs 1 and 2.

In Graph 1, the training set shows a good performance with an R^2 value of 90% in the models established according to the return on assets variable. The fact that the validation set also performs close to the training set can be interpreted as the model is well trained and has no fitting problem. The fact that the test set has a value above 80% shows that the generalization and prediction ability of the model is good. The overall performance of the model was realized as 87.



Graph 1. B1 Return on Assets Training, Validation, Test Set, and Overall Performance Error Scatter Graph

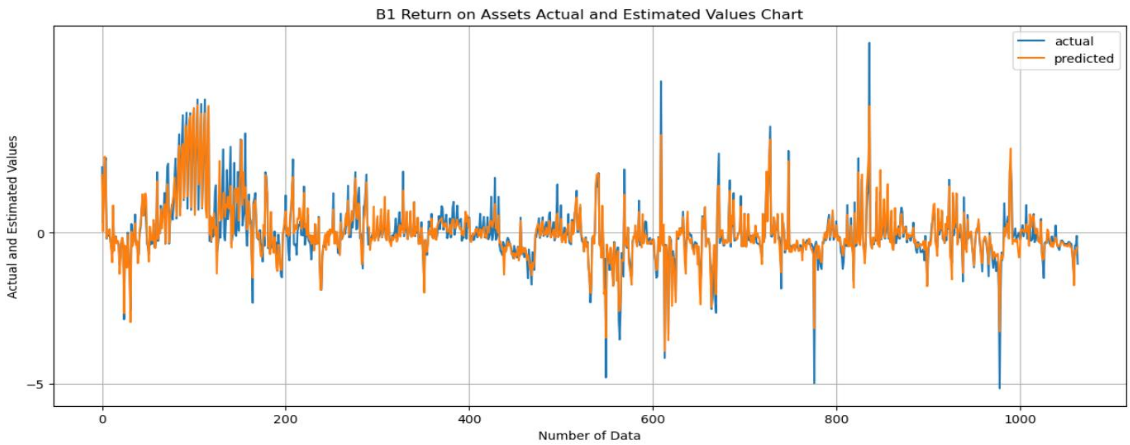
According to Graph 2, the best performance for the ROE variable belongs to the training set with 98%. The validation set, which performs around 94%, shows that the model fits very well. This shows that no overfitting or underfitting was encountered in the model and that the model was trained quite well. The test set with an R^2 value of 96% indicates that the real data and the prediction data are well matched and the prediction success of the model is high. The overall performance of the model was 98%.



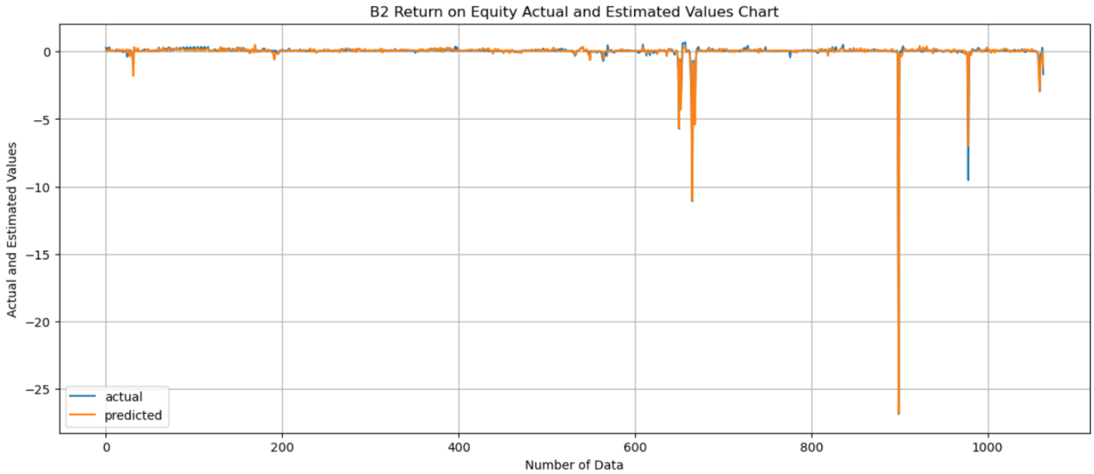
Graph 2. B2 Return on Equity Training, Validation, Test Set, and Overall Performance Error Scatter Graph

The models established for profitability prediction were found to have a high success rate. Accordingly, the agreement between the actual and predicted values of return on assets and ROE variables are given in Graph 3 and Graph 4.

Graph 3 and Graph 4 show that the actual and forecast values of the data set are quite close to each other. Many factors are effective for profitability prediction. Considering that only financial statement data are used for the 17 independent variables used for the analysis, it is seen that the prediction performance in explaining return on assets and ROE is successful.



Graph 3. B1 Return on Assets Actual and Predicted Values Deviation Graph



Graph 4. B2 Return on Equity Actual and Predicted Values Deviation Graph

It has been observed that the selected explanatory variables provide better results in predicting ROE. This situation can be explained by the fact that, as seen in Turkey, real estate investments increase in value over time, and this increase in value leads to a rise in the equity of REITs, thereby enhancing firms' ROE. Additionally, REITs often rely on debt financing for their real estate investments, which brings interest costs. However, if the income generated from REIT investments exceeds the borrowing costs, ROE may increase. The leverage effect resulting from debt financing can enhance equity returns.

5. Comparison of Models

Table 10 presents the comparison findings for the results of both prediction analyses. According to Table 10, the MLP Regressor model, established to predict return on assets and ROE, obtained better results. According to the regression models, the models predicting ROE yielded the best R^2 result. The overall performance value of R^2 for the MLP Regressor model for the prediction of return on assets is 87%, while the R^2 value for the Driscoll-Kraay robust fixed effects model is 55%. For the prediction of ROE, the MLP Regressor model results in an overall performance value of R^2 of 98%, while the R^2 value for the Driscoll-Kraay robust fixed effects model is 73%. While the MAE metric gives the least error for the Driscoll-Kraay robust fixed effects model, the MSE metric gives the least error for the MLP Regressor model. Compared to the Driscoll-Kraay robust fixed effects model, the MLP regressor model has better prediction performance. This can be interpreted that the MLP regressor model performs a good learning from the data by using the parameters.

Table 10. Comparison of Driscoll-Kraay Robust Fixed Effects Model and MLP Regressor Model

	B1- Return on Assets		B2- Return on Equity	
Performance Metrics	**Driscoll-Kraay Resistive Fixed Effects Model**	**MLP Regressor**	**Driscoll-Kraay Resistive Fixed Effects Model**	**MLP Regressor**
MSE	-	0.12316	-	0.01824
MAE	0.000001908	0.22403	0.00015062	0.07396
RMSE	-	0.35095	-	0.13509
R^2	0.5578	0.87683	0.7266	0.98175

6. Conclusion, Discussion and Recommendations

The analyses conducted using the Driscoll-Kraay Robust Fixed Effects Model, a panel data analysis technique, and the MLP Regressor model compared both methods. For profitability prediction, the study employed the MLP Regressor (Multilayer Perceptron Regressor) algorithm, one of the machine learning techniques based on ANN. Accordingly, the objective of the study is to identify the best model for profitability prediction by comparing the findings obtained from REITs listed on BIST, which hold a significant market share, using the MLP Regressor algorithm and the Fixed Effects Model, a traditional econometric method within panel data analysis techniques. Within the scope of the study, return on assets (ROA) and ROE were used as dependent variables for profitability prediction. ROA reflects the profitability derived from a firm's total assets, while ROE indicates whether companies effectively utilize their equity and demonstrates their growth strategies. Both variables are critical for assessing firms' financial health, potential risks, and performance. They are particularly significant as guiding factors for strategic decision-making in REIT firms.

The scope of the research encompasses 27 REITs listed on BIST during the quarterly periods from 2010 to 2019. The analysis is limited to data from 2010 to 2019 due to the economic crisis prior to 2010 and the rapid increase in real estate prices following the pandemic in 2019, which define the boundaries of the study. Additionally, out of 48 REITs listed on BIST, only 27 with complete and accessible data were included in the analysis, representing another limitation of the study. It is evident that the MLP Regressor analysis provides a prediction result closer to the actual values compared to the Fixed Effects Model. The explanatory power of the ANN analysis is strong for both dependent variables. This can be attributed to the ANN's ability to effectively model complex and nonlinear relationships, as well as its capacity to handle outliers and missing data while maintaining a strong learning capability.

A review of the literature reveals that ANN outperform traditional methods such as linear regression. For instance, Schöneburg (1990) predicted stock prices with 90% accuracy, while subsequent studies (Desai and Bharati, 1998; Saberi et al., 2016) highlighted the strong predictive capability of ANNs in financial indicators. The findings of this study align with previous research, demonstrating that ANNs exhibit superior predictive power compared to traditional models.

This study stands out as one of the limited works in the literature comparing ANN and panel data analysis methods. Similar to the studies conducted by Heo et al. (2020) and Ho et al. (2020), this research has found that ANN-based algorithms outperform traditional econometric models in prediction accuracy. This result aligns with other studies in the literature, highlighting ANN's ability to effectively model complex and nonlinear relationships. For instance, the findings of Kıral and Çelik (2020) and Parlakkaya et al. (2022) revealed discrepancies between panel data analysis and ANN outcomes, with ANN demonstrating stronger predictive success. This advantage is particularly attributed to ANN's capability to handle diverse data types and effectively manage outliers, further supporting its superiority.

In the literature, the number of studies that combine ANN analysis with panel data analysis is quite limited. Future research could integrate these two methods using hybrid models to obtain more robust and comprehensive results. Additionally, the success rate of ANN models is closely related to the size of the dataset and the selection of independent variables. For instance, Saberi et al. (2016), Lado-Sestayo and Vivel-Bua (2020), Alaameri and Faihan (2022), and Vukovic et al. (2023) achieved high accuracy rates by utilizing deep learning models. In this context, it is recommended that deep learning techniques be more extensively employed in predicting corporate profitability in Turkey.

The findings obtained from this study provide valuable insights for investors and REIT firms. From an investor’s perspective, profitability forecasting is crucial as it allows for a comprehensive assessment of REIT firms' performance, thereby guiding investment decisions. Measuring key indicators such as ROA and ROE enables investors to evaluate firms' profitability potential, growth expectations, and risk analysis. As confidence in highly profitable and sustainable REITs increases, investment decisions can be made more efficiently in terms of time and cost. For REIT firms, profitability forecasting plays a critical role in strategic planning and portfolio management. These forecasts facilitate the optimization of financial performance, the identification of growth opportunities, and the development of new projects. Moreover, by analyzing the impact of hyperparameters and weights on profitability through established models, more effective modeling and forecasting can be achieved, serving as a guide for both new investors and existing REIT managers. The findings obtained are significant for creating a competitive advantage and ensuring sustainable success in the REIT sector.

In conclusion, this study demonstrates the advantages of employing ANN methods for profitability prediction in the REIT sector by linking its findings to the limited existing literature. The results indicate that future analyses could benefit from utilizing ANN and other machine learning techniques with broader datasets and deep learning methods to enrich REIT analyses. This approach not only contributes to the academic literature but also provides more flexible and reliable modeling opportunities for practical applications in the industry. Better prediction performance can be achieved with the use of machine learning algorithms and techniques created for profitability prediction. This allows investors to make more reliable, updatable, and faster predictions in the future. Thus, it can automate many steps in issues such as data preprocessing, variable selection, and modeling processes that require expertise. Machine learning algorithms also offer companies the opportunity to make flexible modeling due to their ability to adapt to different data types and structures. Thanks to its ability to make predictions by updating in real-time, to analyze data flows, and to adapt to changing conditions faster, machine learning is expected to be used for different purposes in the future, providing faster and more reliable results and increasing its importance and the benefits it will provide. The results indicate that future analyses could benefit from utilizing ANN and other machine learning techniques with broader datasets and deep learning methods to enrich REIT analyses. It can be suggested that more applications be conducted using broader data models in the REIT sector, where there is a noted gap in the use of deep learning methods in the literature. This approach not only contributes to the academic literature but also provides more flexible and reliable modeling opportunities for practical applications in the industry.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest
There is no potential conflicts of interest in this study.

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