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Estimating Financial Failure in Businesses Using Artificial Neural Networks: Turkish Manufacturing Industry Model Study

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Abstract: Businesses need to be financially successful to achieve sustainable growth and maximise firm value. The financial failure of businesses is a situation that is carefully monitored by business managers, shareholders of the business, financial institutions that lend to the business, and the government. For this reason, in this study, the financial failure of 153 manufacturing companies operating in Turkey and traded on Borsa Istanbul has been tried to be estimated. In the research, the annual financial statements between the years 2009-2021 were used and artificial neural networks were preferred as the estimation method. Altman's Z score was used to define financial failure. In the artificial neural network model, 13 financial ratios were used as input variables. As the output variable, the firms that were below the value of 1.81 calculated as the Z score by Altman were considered unsuccessful, and the unsuccessful firms were assigned a value of 1 and the others a value of 0. This dummy variable consisting of 0 and 1 values is accepted as the output variable. According to the findings of the study, 1427 of 1631 observations that were initially considered to be financial failures were correctly estimated and a very high success rate of 87.49% was achieved. The findings will provide an important advantage to businesses and all stakeholders in terms of determining the causes of financial failure in advance.

Keywords: Financial failure; Altman Z score; Artificial neural networks; Borsa Istanbul

1. Introduction

To maintain their existence in a globally competitive environment and to maximise their market value, businesses must make a profit from the assets they hold (Madrid-Guijarro et al., 2011; Opler & Titman, 1994). With the financial crises experienced, the concept of financial failure has gained importance in businesses. The concept of financial failure has been an important research area that maintains its importance from the past to the present and has been the subject of many academic studies (Habib et al., 2020). It was first analysed with the model developed by Altman (1968). Since the model is based on financial statement data, it has been used frequently in the measurement of financial failure because it has both a reliable and easy application area.

Although the concept of financial failure appears with different definitions in the literature (Bas & Cakmak, 2012; Kulali, 2016; Ohlson, 1980), it can be expressed as the inability of businesses to fulfil their financial obligations in the expected time or experiencing difficulties while fulfilling their obligations, in addition to being expressed with the concept of bankruptcy (Açikgöz, 2012; Arslan, 2019; Platt & Platt, 2006). When the literature is examined in depth, it has been stated that financial failure in enterprises may be caused by internal reasons, and many external reasons are important in this process (Gilson, 1989; Sri, 2016; Uzun, 2005). External factors, it is expressed as the inability to keep up with economic, political, political changes and technological changes (Sevim & Pasli, 2018).

The financial failure experienced on a micro basis causes effects at the macro level. Bankruptcies in businesses, which are the cornerstone of the economy, deeply shake the country's economies. From these perspectives, predetermining the causes of financial problems in enterprises and producing solutions will make a positive contribution to the country's economy both in micro and macro terms.

This study aims to create a model that will predict the risks of bankruptcy in enterprises, which are an important economic unit, and strengthen the enterprises financially, thanks to the model created. For this purpose, the financial ratios of the manufacturing enterprises traded in BIST for the years 2009-2021 were taken as data and analyses were carried out.

1.1 The Concept of Financial Failure, Its Causes and Models Used in Predicting Financial Failure

1.1.1 Financial failure concept and reasons

As mentioned before, the concept of financial failure has been expressed with quite a variety of definitions in the literature. In this part of the study, how the concept of financial failure is defined by various authors and the factors that lead to financial failure in businesses are included.

In the studies conducted in Table 1, definitions of businesses that are financially unsuccessful are included and it has been observed that financial failure is generally associated with the concepts of insolvency, going into default and bankruptcy.

Table 1. Financial failure definitions

Author, Date	Definition
Altman et al. (2017)	"Lack and inadequacy; bankruptcy, bankruptcy".
Nouri & Soltani (2016)	"Problems faced by businesses as a result of their inability to effectively manage their activities".
Bhattacharjee & Han (2014)	"Having a large amount of debt and problems in repayment"
Dunnan (1986)	"Cessation of activities, bankruptcy, inability to pay debts, the start of enforcement proceedings"
Brigham & Ehrhardt (2010)	"The total value of the cash flows is less than the expected value"
Beaver et al. (2010)	"Filing for bankruptcy within a year"
Coskun & Sayilgan (2008)	"The inability of the cash inflows provided to meet the obligations"
Torun (2007)	"Closing of the board in the stock market"
Altman & Hotchkiss (2006)	"The process of applying to the court for the appointment of a trustee and restructuring of debts has begun"
Aktas (1993)	"Businesses that have made a loss for three consecutive years and whose production has come to a standstill"

The causes of financial failure in businesses are grouped under two headings and these are classified as internal and external factors (Ertuğrul Ayrancı, 2019).

(1) Internal Factors Causing Financial Failure: It is possible to classify the internal factors that cause financial failure in businesses as business-related reasons. Business-related reasons; for management can be expressed in terms of high borrowing and capital insufficiency, and ineffective use of assets (Açıkgöz, 2012; Gör, 2019; Thim et al., 2011). Management-related reasons play an important role in financial failure in businesses. It is known that managers play a key role in maximising business values and profitability. However, in strategic decisions that need to be taken in this key role, wrong decisions can be made due to both lacking information and a lack of coordination (Cornaggia et al., 2017; Khajavi & Ghadirian-Arani, 2018). In some cases, failure problems arise because the managers do not act under the rules or ethically. Another internal factor causing financial failure is the lack of capital and the ineffective use of assets. To increase productivity in enterprises, especially short-term assets should be used effectively and efficiently. In some cases, assets cannot be used effectively and efficiently due to insufficient capital or other problems. Failure to collect receivables on time due to the implementation of wrong receivables collection policies (Akgün, 2002; Mian & Smith Jr, 1992), the weakening of cash power due to idle stocks (Krupp, 1997; Türk & Şeker, 2011), the disruption of production due to inadequate supply management and the result of this. The emergence of customer losses (Kim et al., 2005) is among the examples that can be given to the inability to manage assets effectively. Insufficient capital in enterprises causes debts not to be paid in due time, which leads to serious bottlenecks. Another business-related reason is that the firm is over-indebted. In the financial literature, the indebtedness of the enterprises is determined by the leverage ratio, and it is stated that enterprises with high debt are risky and externally dependent (Bilen & Kalash, 2020). Of course, borrowing is considered normal in cases where investment will be made, and even more, it is said that this is an advantage for the enterprise if the return on the investment is higher than the cost of the debt. However, the use of debt to meet daily activities or to close other debts causes financial failure (Turaboğlu et al., 2017). The fact that the loan/equity ratio of the enterprise is above a certain level indicates that it is excessively indebted and urgent measures are required here.

(2) External Factors Causing Financial Failure: In some cases, financial failure may occur due to non-operational reasons, even though all the conditions are met in the enterprises or there are no structural and financial problems. It is possible to specify the external factors that cause financial failure mainly economic, political, and

legal factors and technological reasons (Ertan & Ersan, 2018). The cyclical fluctuations experienced, increases in exchange rates, increases in interest rates and taxes can put businesses in a difficult situation and this causes financial failures. Political decisions taken can cause serious customer losses for businesses. Foreign trade policies, tax practices and sanctions applied in some cases cause customers to lose customers (Yarış & Kanik, 2021). At the same time, neglecting the legal regulations enforced by the state leads to legal sanctions, fines, and loss of reputation. Another external factor that causes financial failure in businesses is the inability to keep up with technological changes. Businesses cannot keep up with technological changes due to both cash shortages and conservative management, and this may lead to bankruptcy by weakening their market share (Ağırman, 2018).

1.1.2 Models used in predicting financial failure

In this part of the study, models used to measure financial failure are included.

(1) Altman Z score Model: The model developed by Edward Altman in 1968 took an important place in the literature as the first model used to measure financial failure and has led to many studies today. In the model, a Z score was determined by using certain ratios of the enterprises and reference intervals were determined according to the Z score values found. According to the reference intervals, the enterprises are divided into three classes: successful, unsuccessful, and non-informative enterprises. In the study, the Z score was calculated with the help of the following formula.

$$Z= 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4+ 0.99X_5 \tag{1}$$

X_1= Net Working Capital/Total Assets
X_2= Retained Profits/Total Assets
X_3= Profit Before Interest and Tax/Total Assets
X_4= Current Value of Equity/Book Value of Loans
X_5= Net Sales/Total Assets
Z-score reference intervals were determined as follows.
$Z > 2.99$; Successful
$1.81 < Z < 2.99$; Doesn't Provide Information About the Business
$Z < 1.81$ Unsuccessful.

(2) Springate Model: Another important model used to predict financial failure was developed by Springate in 1978. In the model, unlike Altman (1968), the author used four financial ratios. The model equation that Springate uses is presented below.

$$S= 1.03A + 3.07B + 0.66C + 0.4D \tag{2}$$

A= Working Capital/Total Assets
B= Profit Before Interest and Tax/Total Assets
C= Profit Before Interest and Tax/Short-Term Loans
D= Sales/Total Assets
If $S< 0.862$, companies are considered to be unsuccessful.

(3) Fulmer Model: In the model created by Fulmer et al. (1984), financial failure was tried to be estimated by using nine financial ratios belonging to businesses. The formula for calculating the H value he used in his studies is given in equation number three below.

$$H= 5.528D_1 + 0.212D_2 + 0.073D_3 + 1.270D_4 – 0.120D_5 + 2.335D_6 + 0.575D_7 + 1.083 D_8 + 0.894D_9 – 6.075 \tag{3}$$

D_1= Retained Profit/Total Assets
D_2= Sales/Total Assets
D_3= Profit Before Tax/Equity
D_4= Cash/Total Loans
D_5= Total Loans/Total Assets
D_6= Short Term Loans/Total Assets
D_7= Logarithm of Tangible Fixed Assets
D_8= Working Capital/Total Loans
D_9= Log Interest and Pre-Tax Profit/Interests
If $H < 0$; The business is considered unsuccessful.

2. Literature Review

Many studies have been conducted in the financial literature to detect the financial failures of businesses. These studies and the findings obtained from these studies are given below.

Beaverf Springate (1966) identified successful and unsuccessful businesses by using data from 1954 and 1964 to examine the effect of financial ratios on financial success. Using discriminant analysis as an analysis method, the authors observed that the financial ratios of companies with high liquidity and credibility are also in good condition.

Altman divided financial ratios into five basic groups in his 1968 study. He identified five basic group distinctions as liquidity, profitability, efficiency and leverage, and business value ratios. In this study, Altman calculated the Z basic value mathematically and described the businesses below a certain threshold value as unsuccessful. Using discriminant analysis as an analysis method, the author identified 33 successful and 33 unsuccessful businesses, used 22 financial ratios and determined the accuracy of the model as 95%.

Springate (1978) determined the S value by using four basic ratios in his study and considered businesses with an S value below 0.862 as unsuccessful.

Odom & Sharda (1990) tested the financial failure predictions of 129 companies operating in 1975-1982 using artificial neural networks and discriminant methods. According to their results, they have seen that the artificial neural network method is more successful in predicting bankrupt companies.

Aktaş et al. (2003) in their study, took the financial ratios of industrial and commercial enterprises traded in the ISE between 1983-1997 as data. Artificial neural networks, multiple regression analysis, logit regression analysis and discriminant analysis were used as analysis methods. In their findings, they found that the most effective model for predicting financial failure is the artificial neural network model.

Altaş & Giray (2005) used the 2001 financial ratios of textile companies traded in the ISE in their study and tried to determine the risks of financial failure. The authors, who used factor analysis and logistic regression models as analysis methods, determined the success of the model they developed as 74%.

Benli (2005), in his study, compared the artificial neural network model used to predict financial failure in businesses and logistic regression models and used the data of 49 banks operating between 1997-2001 and transferred to the fund for this purpose. His studies concluded that the artificial neural network model was more successful in predicting failure (82.4%) than the logistic regression model (71.6%).

In their study, İçerli and Akkaya (2006) took as data the financial ratios of 40 successful and 40 unsuccessful enterprises operating in the service, transportation, and financial sectors, traded in the ISE between 1990-2003. The authors applied the Z test to 80 enterprises and differences were determined in terms of current ratio, acid-test ratio, and receivables turnover ratio in terms of two groups of enterprises. They also concluded that there is no significant difference between successful and unsuccessful businesses in terms of cash ratio, VAT/Total Assets, asset turnover, inventory turnover and profitability ratios.

Chung et al. (2008) used 36 financial ratios in their study and took New Zealand businesses as data. Using discriminant analysis and artificial neural network methods as analysis methods, the authors concluded that the ratios used in determining the risk of financial failure are effective.

Lin (2009) used 20 financial ratios belonging to businesses in his study and used discriminant, logit-probit and artificial neural network analysis as analysis methods. Testing the classification success of the methods used, the author found that the logit method achieved the most successful results.

Çelik (2010) compared the predictive power of traditional methods and artificial neural network models in predicting financial failure. Working with 36 private banks, the data of which she could access, the author concluded that the prediction percentage of the artificial neural network model is relatively high compared to other methods.

Terzi (2011) calculated the financial failure risk of food businesses traded in the ISE. They applied the Z score test to identify financially unsuccessful businesses. Using 19 financial ratios, the author used discriminant analysis in his study and stated that his model had an accuracy rate of 90.9%. As a result of the findings obtained by the author, it was concluded that the most important variables in financial success are return on assets and leverage ratio.

Halim et al. (2011) Taking 17 financial ratios of businesses operating in Malaysia as data, the authors divided the ratios into four groups. As a result of the analysis, they concluded that the financial ratios used are important indicators of the failure of the enterprises.

Buyukarikanf (2014) examined the financial failures of businesses with the Altman Z-Score method and Springate methods in their study. As data, the financial ratios of the companies operating in the IT sector traded in the BIST for the years 2008-2013 were used and they concluded that the bankruptcy risk cannot be predicted only with financial ratios, and management factors may also be significantly effective.

Selimoğlu & Orhan (2015) used 23 financial ratios belonging to textile, clothing and leather businesses traded on the BIST in their study. The authors, who reached the finding that 7 of the 23 ratios used showed significant differences for successful and unsuccessful groups, used discriminant analysis as the analysis method and concluded that the success of the model was 92%.

Karaca & Özen (2017) examined the relationship between the financial failures of companies that make up the Tourism index in BIST and the change in stock prices. In the study covering the years 2009-2016, financial failure was modelled using the Altman Z score. According to the findings of the studies, no significant relationship was found between financial failure and the change in stock prices. Again, it was concluded that the risk of bankruptcy of companies in the tourism sector increased in 2015-2016.

Tian & Yu (2017) used 29 financial ratios of Japan and European countries for the years 1998-2012 in their study. The Z score model was used to detect financial failure. As a result of the study, it has been found that the risk of financial failure is low in businesses that have better equity/total loan, leverage ratio, and short-term loans/sales income ratios for businesses operating in Japan.

Kuzu (2017) used 18 financial indicators of 24 companies operating in different industries traded in BIST as data. In his study, he concluded that the percentage of predicting financial failure of the artificial neural network model is around 71% when financial indicators are taken into consideration at the time of crisis.

Jaafar et al. (2018) tried to examine the relationship between financial failure risks and financial ratios of businesses operating in Malaysia. The Altman Z score test was used to identify financially unsuccessful businesses, and they concluded that businesses with a high return on assets have a low risk of financial failure, but businesses with high leverage have increased financial failure.

In his study, Ertuğrul Ayrancı (2019) took 26 financial ratios of 155 industrial enterprises traded on the BIST for the period 2019.Q2 as data and divided the data into 5 groups. The author, who used factor analysis, logistic regression, and the Williams method in his study, used variance explanation powers in the detection of financial failure. In the findings he obtained, he concluded that the Williams method is more effective and the most important variable group that affects financial success or failure is the liquidity ratios.

In their study, Çöllü et al. (2020) used the financial ratios of businesses operating in the textile, clothing and leather industries traded in BIST between 2016-2018 and determined which variables affect financial failure. He used the Altman Z score test to determine which of the 20 businesses were successful, and by using data mining algorithms, it was found that the current ratio, the ratio of fixed assets to equity, the ratio of trade receivables to assets, inventory turnover and interest coverage ratio were effective on financial success, respectively.

In the research of Karadeniz et al. (2021), the financial ratios of 63 accommodation businesses from 19 countries in Europe were taken as data for the years 2012-2019 and the Fulmer H score value was used to identify unsuccessful businesses. The authors' used return on assets, business size and market value/book value as independent variables. The findings they obtained were that the financial success of the enterprises with a high return on assets and business size increased, but the market value/book value ratio did not have any effect on the risk of financial failure.

Kaplanoğlu & Moroğlu (2021) analysed the financial failures of manufacturing industry companies traded in BIST in 2019 and 2020 during the COVID-19 period. Altman (1968), Springate (1978), and Fulmer et al. (1984) models were used for financial failure in the research. According to the findings of the research, a decrease was observed in the number of financially failed companies in both 2019 and 2020 during the COVID-19 period of manufacturing industry companies. According to the findings of the research, a decrease was observed in the number of financial failure companies in both 2019 and 2020 during the COVID-19 period of manufacturing industry companies.

The financial ratios for the years 2004:6-2019:12 of the metal goods traded in the BIST were used and the effect of these financial ratios on the financial failure was tested (Yaman & Korkmaz, 2021). In their studies, models of Altman (1968), Fulmer et al. (1984), Ohlson (1980), and Springate (1978) were used to detect financial failure. Panel data analysis was used as the analysis method, and it is seen that the working capital variable affects financial success.

In their study, Kendirli & Citak (2022) used the financial ratios of the enterprises operating in the Forest, Paper and Printing Index traded in BIST between the years 2016-2020 and determined the financially unsuccessful enterprises with the Altman Z score method. As a result of the research, it has been estimated that 7 of the 15 companies in the index have a high risk of bankruptcy.

When the studies on financial failure in the literature are examined, either the factors causing financial failure have been analysed or the financially unsuccessful businesses have been tried to be determined beforehand. In addition to traditional methods such as factor analysis, discriminant analysis, and logistic regression, machine learning methods such as artificial neural networks were used in financial failure prediction. The aspect that distinguishes this research from other studies in the literature is that it will contribute to taking necessary measures by predicting the financial failures of the manufacturing industry enterprises that are indicative of the Turkish economy and that are listed on the stock exchange after the 2008 global crisis (mortgage).

3. Model Specification

In the study, 198 manufacturing enterprises traded in BIST are discussed. Of the enterprises included in the analysis, 33 are in the food and beverage industry, 26 in the textile and clothing industry, 13 are in the paper and forest products industry, 43 are in the chemical and pharmaceutical industry, 22 are in the cement industry, 25 in the basic metal industry and 36 in the metal goods and equipment industry. In the study, 5 financial ratios were obtained by using the financial statements of 153 manufacturing companies between the years 2009-2021, the data of which were available at the same time and were used to calculate Altman's Z score.

13 financial ratios determined out of these 5 financial ratios are included in the model as an independent variable (input) for the estimation of financial failure in the financial literature. Financial failure was predicted with artificial neural networks, which is a machine learning method, and Matlab R2017b software was used in the prediction process with artificial neural networks.

The financial ratios used in the calculation of the Altman Z score and the financial ratios included in the model as input variables are shown in Table 2.

Businesses that are below the threshold of 1.81 determined according to the Altman Z score of manufacturing enterprises traded in BIST are considered financially unsuccessful. 1 for businesses deemed financially unsuccessful; For the others, a dummy variable with a value of 0 was included in the model as an output variable, and then it was estimated by artificial neural networks, which is a machine learning method. Descriptive statistics of input and output variables are shown in Table 3.

Table 2. Variables and types

Variable	Type
Net Working Capital/Total Assets	Fails if Z-score<1.81 (Output Variable)
Retained Profits/Total Assets	
Profit Before Interest and Tax/Total Assets	
Current Value of Equity/Book Value of Loans	
Net Sales/Total Assets	
Current Ratio-(Current Assets/Short-Term Liabilities)	Input Variable
Acid Test Ratio-(Current Assets-Inventories/Short-Term Liabilities)	
Cash Ratio-(Liquid Assets+Stocks/Short-Term Liabilities)	
Total Loans/Equity	
Short-Term Loans/Total Loans	
Interest Coverage Ratio- (Operating Income /Interest Expense)	
Receivable Turnover Rate-(Net Sales/Average Trade Receivables)	
Stock Turnover-(Cost of Sales/Average Stocks)	
Current Asset Turnover Rate-(Net Sales/Current Assets)	
Active Turnover Rate – (Net Sales/Total Assets)	
Return on Assets (ROA)-(Net Profit/Total Assets)	
Return on Equity (ROE)-(Net Profit/Total Equity)	
Market Value/Book Value	

Table 3. Descriptive statistics of variables

Financial Ratio	Survey	Average	SD	Minimum	Maximum
Net Working Capital/Total Assets	1989	0.2360	0.1681	0	0.8005
Retained Profits/Total Assets	1989	1.9142	3.9510	0	34.9323
Profit Before Interest and Tax/Total Assets	1989	10.3121	9.8805	-52.1663	84.1899
Current Value of Equity/Book Value of Loans	1989	1.6883	2.8132	-0.8847	56.3986
Net Sales/Total Assets	1989	0.8983	0.5260	0	7.8556
Current Ratio	1989	1.9825	2.0382	0	43.8636
Acid Test Ratio	1989	1.2932	1.1604	0	35.0552
Cash Ratio	1989	43.6613	102.0015	0	1495.1390
Total Loans/Equity	1989	190.5460	1397.2120	-17382.7900	55486.7700
Short-Term Loans/Total Loans	1989	72.0386	18.5738	0	99.8956
Interest Coverage Ratio	1989	80.7286	2759.6430	-784.7022	122001.9000
Receivable Turnover Rate	1989	5.9707	6.5881	0	174.7393
Stock Turnover	1989	7.4502	35.6775	0	1140.1640
Current Asset Turnover Rate	1989	0.9686	0.5626	0	6.7688
Active Turnover Rate	1989	1.8764	0.9776	0	9.8610
Return on Assets (ROA)	1989	4.4684	17.0622	-119.3264	571.4781
Return on Equity (ROE)	1989	5.0404	62.8116	-1572.3240	1235.5770
Market Value/Book Value	1989	2.7813	8.9417	0	317.9661

Artificial Neural Networks

The complexity and non-linearity of financial variables enable the predictions with artificial neural networks to give even more effective results. Artificial neural networks are non-dispersed, network-shaped, and non-linear circuits (Özer et al., 2018). Artificial neural networks are computer software that performs basic functions such as generating new data from the data collected by the brain through learning, remembering, and generalising by imitating the learning path of the human brain (Öztürk & Şahin, 2018; Yavuz et al., 2020). In other words, artificial neural networks emerged because of the mathematical modelling of the learning process inspired by the human brain (Öztürk & Şahin 2018; Yavuz et al., 2020). The difference between biological neural networks and artificial neural networks is shown in Figure 1.

In a sense, artificial neural networks can be thought of as parallel information processing systems. This information is given to the artificial neural networks by training on the examples of the relevant event. Thus, by making various generalisations on the features revealed by the examples, it produces solutions to events that will emerge later or that have never been encountered before (Aygören et al., 2012).

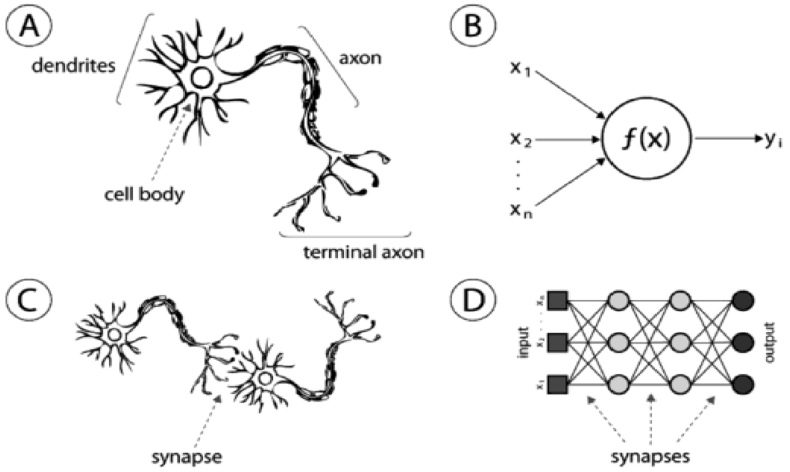

Figure 1. Comparison between biological neural networks and artificial neural networks
A: Human neuron; B: Artificial neuron; C; Biological synapse; D: ANN synapses
Source: Maltarollo et al. (2013)

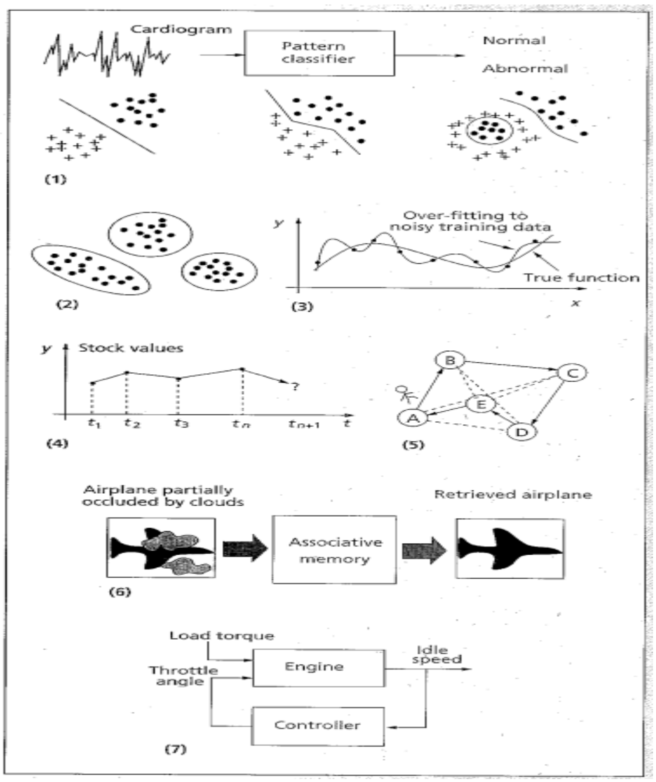

Figure 2. Artificial neural networks application areas
(1) *Pattern classification;* (2) *Clustering/categorization;* (3) *Function approximation;* (4) *Prediction/forecasting;* (5) *Optimization;* (6) *Retrieval by content and* (7) *Control*
Source: Jain et al. (1996)

Artificial neural networks can be applied in many areas such as Pattern classification, clustering/categorization, function approximation, Prediction/forecasting, Optimization, Content-addressable memory, and Control. The usage area of artificial neural networks is shown in Figure 2.

Learning in artificial neural networks occurs by changing the weight coefficients of the link between inputs and outputs (Öztürk & Şahin, 2018). The weights are determined randomly at the beginning so that the system is not locked at the starting point (Kutlu & Badur, 2009). An artificial neural network consists of many processing units called neurons. In general, neurons are in logical groups called layers. The network has a hierarchical structure consisting of three or more layers. This network has 1 input, 1 or more hidden layers and 1 output layer (Kutlu & Badur, 2009). The schematic representation of the artificial neural network architecture is shown in Figure 3.

The biggest problem in artificial neural networks is that it needs multi-layered and multi-neuron artificial neural networks to solve complex problems (Yakut et al., 2014). Artificial neural network applications are mostly used in prediction, classification, data association, data interpretation and data filtering (Öztürk & Şahin, 2018).

Artificial neural network models are examined in four groups: single-layer perceptrons, multi-layer perceptrons, feed-forward artificial neural networks and feedback artificial neural networks (Kantar, 2020; Öztürk & Şahin, 2018). Since the aim of the study is not artificial neural networks, the method will not be discussed in detail.

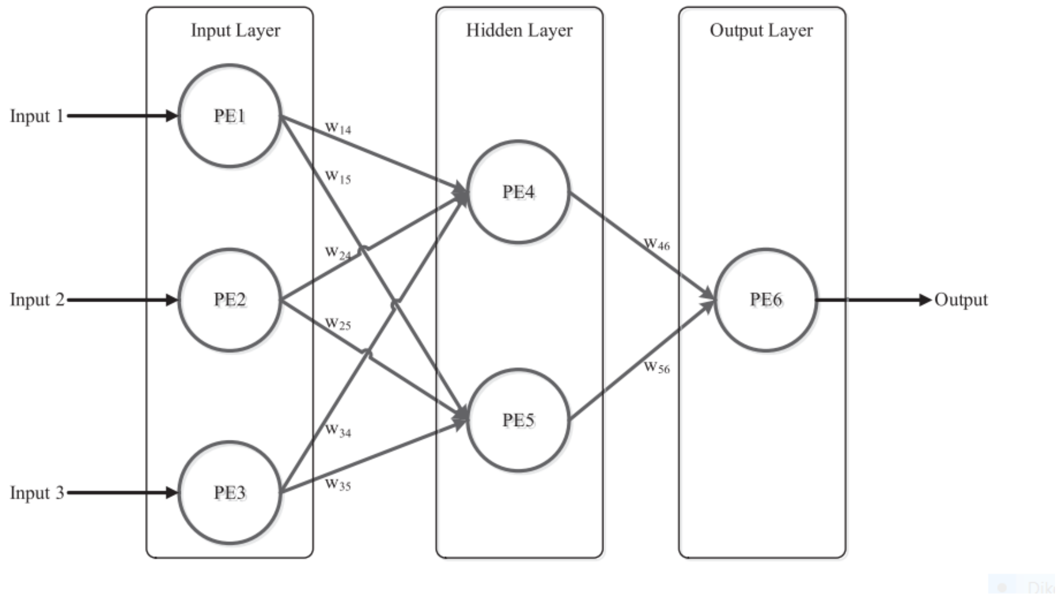

Figure 3. Artificial neural network architecture
Source: Fadlalla & Amani (2014)

4. Empirical Finding

To determine financial failure, 13 financial ratio input variables, the first ten hidden layers, and the dummy variable with an Altman Z score value below 1.81, which is assigned a value of 1, and the others with a value of 0, are included in the model as an output variable, and then financial failure is estimated with artificial neural networks. Figure 4 shows a two-layer feedforward neural network architecture with 13 input variables and one output variable.

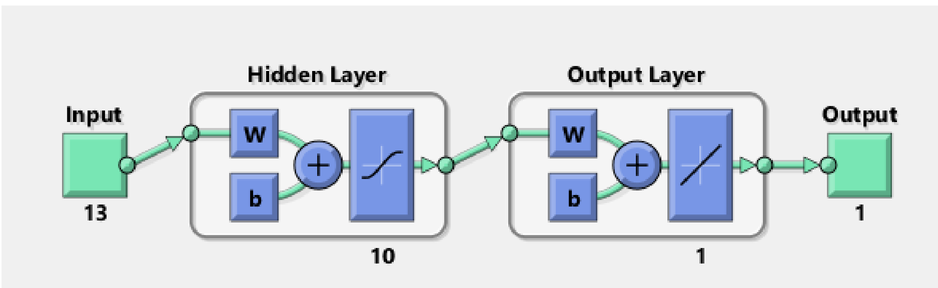

Figure 4. A two layer-feed-forward network with sigmoid hidden neurons and output neurons

13 financial ratios (current ratio, acid test ratio, cash ratio, total loan/equity, short-term loans/total loans, interest coverage ratio, receivables turnover, inventory turnover, current asset turnover, asset turnover, ROA, ROE, market value/book value) were used as the input variable shown in the artificial neural architecture in Figure 4. In the hidden layer, 10 neurons were used, and the dummy variable was used as the output variable, which was accepted as the Altman Z score of 1.81, which was assigned a value of 1 for the companies and 0 for the others. 70% of the observations used in the input variables were used for training, 15% for validation and 15% for testing purposes. While determining the best result in artificial neural networks, the highest R-value and the smallest MSE values were considered. Observations included in the model need to be trained repeatedly to get the best results. Again, the number of neurons in the hidden layer in artificial neural networks can be increased to obtain the best result.

In the artificial neural networks, 1631 of the 1990 observations included in the dummy variable included in the model as an output variable were below the 1.81 threshold value, which is the criterion of financial failure. The research aims to predict these companies, which are determined to be unsuccessful according to the Altman Z score, through artificial neural networks with 13 financial ratios (inputs) determined according to the financial literature. The artificial neural network model prediction results are shown in Table 4.

According to the test results shown in Table 4, the model using 20 neurons in the hidden layer was preferred as the most appropriate prediction model since it had the highest R-value and the lowest MSE value according to all test results. The best validation performance is shown in Figure 5.

According to Figure 5, the best validation performance was at Step 88 (Epoch) and the MSE value was 0.038268. The neural network training error histogram is shown in Figure 6.

When the error histogram of the artificial neural network training shown in Figure 6 is examined, it is observed that the errors are concentrated between -0.07231 and 0.0323 values and have successful prediction values since they do not go further than 0. The regression results of the model with 20 neurons in the hidden layer and having the lowest MSE and the highest R-value are shown in Figure 7.

Table 4. Prediction findings of financial failure with artificial neural networks

I. Panel	Training rate %70	Validation rate %15	Testing rate %15
10 Neuron	MSE	R	
Training	2.7094	0.9031	
Validation	3.4778	0.8734	
Testing	5.8993	0.7920	
15 Neuron	MSE	R	
Training	2.6482	0.9082	
Validation	3.8851	0.8761	
Testing	5.0782	0.7951	
20 Neuron	MSE	R	
Training	2.7034	0.9048	
Validation	3.8268	0.8626	
Testing	5.0591	0.8038	

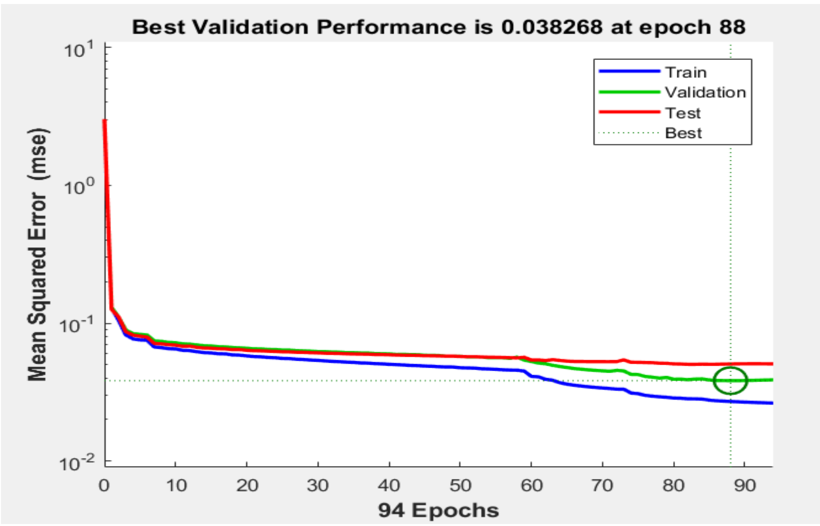

Figure 5. Best validation performance

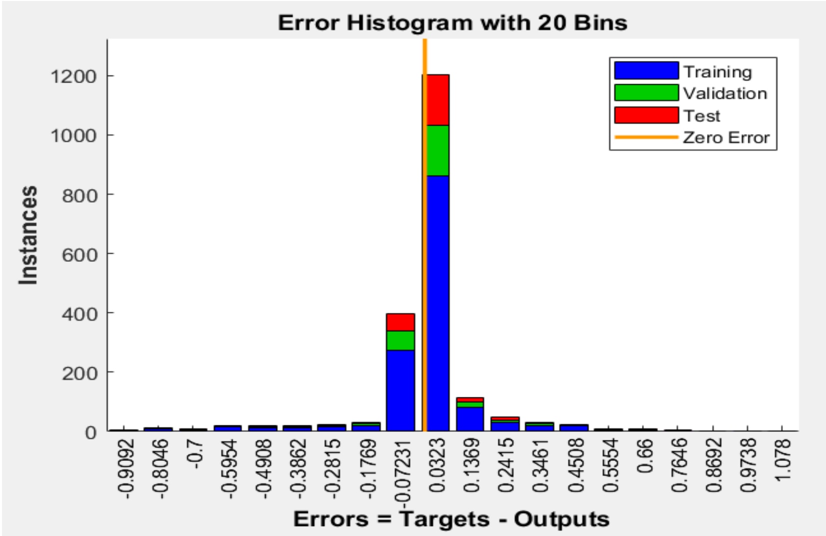

Figure 6. Error histogram

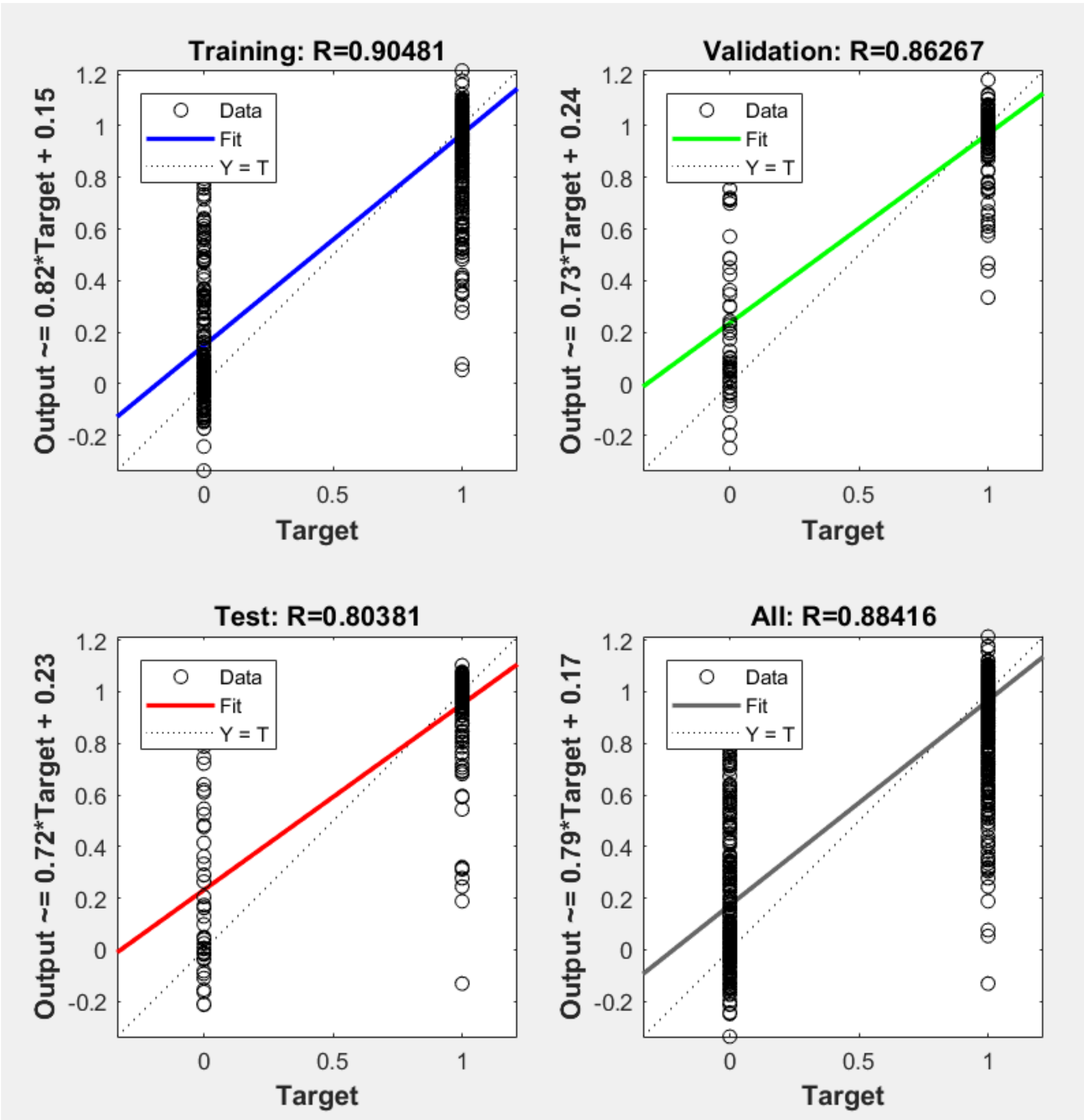

Figure 7. Neural network training regression results

As shown in Figure 7, the best prediction results of the model are the predictions on the line with a 45-degree angle, shown with dashed lines. The R-value of all observations was 0.8841, approaching the value of 1. For this reason, it can be said that artificial neural networks make a successful prediction in the estimation of a non-linear relationship whose output variable is between 0 and 1. The estimation results of successful and unsuccessful observation values according to artificial neural networks are shown in Table 5.

According to the results shown in Table 5, the aim of the study was that financial failure was predicted by artificial neural networks at a rate of 87.49%.

Table 5. Financial failure prediction results with artificial neural networks

Financially Unsuccessful	Prediction Rate
1427/1631	*%87.49*

5. Conclusion

Businesses strive to continue their activities successfully and to maximise firm value. For businesses to maximise firm value, they need to generate steady cash flow. Again, the excess cash flow obtained because of the cash inflows of the enterprises being more than the cash outflows will allow the business to grow and reinvest. Businesses face many risks while continuing their activities. Some of these risks can be listed as currency risk, interest rate risk, and political risk, which is known as market risk. Again, apart from these risks, it is the risk of a pandemic such as the recently encountered COVID-19. In addition to the market risk, there are sector-specific risks, supply chain problems and similar risks, as well as the firm's risks (operational risk, management risk, etc.). Both market risk and specific risks can cause businesses to fail, and this is often referred to as financial failure. There have been many studies on financial failure, and one of the most important of these studies was Altman in 1968. In this study, Altman calculated the Z score from the financial ratios obtained by using various financial statements to detect financial failure. He defined the companies that were below this Z score he found as financially unsuccessful. Financial failure is an important situation that is closely followed by both company owners and shareholders of publicly traded businesses. Again, apart from these two parties, financial institutions, suppliers, and the state are important stakeholders of these enterprises due to their tax receivables. All these stakeholders want businesses to be financially successful. Therefore, predicting financial failure has always attracted the attention of financial literacy. In this study, by using Altman's Z score, the financial failure of 153 manufacturing companies traded in Borsa Istanbul between 2009-2021 was estimated by the artificial neural network method. In the study, 1427 of 1631 observations determined as unsuccessful according to Altman's Z score were predicted correctly. The correct prediction rate of financial failure is 87.49%, Which is similar to the findings of Aktas et al. (2003), Chung et al. (2008), and Lin (2009).

The obtained research findings showed that 13 input variables (current ratio, acid test ratio, cash ratio, total loan/equity, short-term loans/total loans, interest coverage ratio, receivables turnover, inventory turnover, current asset turnover, asset turnover, ROA, ROE, market value/book value) used in the artificial neural network model gave successful results in the prediction of financial failure.

It is extremely important in terms of predicting financial failure and taking precautions for the future, following these companies by financial institutions that lend to businesses that are considered financial failures, tracking tax receivables by the government, and following the value of the stocks owned by the shareholders. For this reason, the prediction of financial failure with artificial neural networks, which is a machine learning method of complex and non-linear financial observations, will make an important contribution to the literature.

Financial ratios obtained from the financial statements of the companies were used to predict financial failure. To increase the forecast performance obtained with the help of artificial neural networks, variables that consider the market risk, as well as the firm-specific variables, can be added to the model as input variables, making a significant contribution to the literature.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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