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CORPORATE BANKRUPTCY PREDICTION USING MACHINE LEARNING METHODS: THE CASE OF THE USA

Asst. Prof. Gerçek ÖZPARLAK
Beykent University, VS, Istanbul, Turkey, *(gercekozparlak@beykent.edu.tr)*

Menevşe ÖZDEMİR DİLİDÜZGÜN, PhD
Halk Investment, Istanbul, Turkey, *(mozdemir@halkyatirim.com.tr)*

ABSTRACT

Being able to predict company bankruptcies is important to protect the continuity of company partners, investors, company creditors and other companies in this sector. Company managers can prevent company bankruptcies by taking the necessary precautions in advance, and investors can limit their losses with accurate bankruptcy forecasts. This study aims to compare the bankruptcy prediction performances of machine learning methods and classical classification methods and to develop models that can predict bankruptcies in the health sector. 103 companies in the health sector that declared bankruptcy between 01.01.2011 and 31.12.2021 in the USA, and 103 companies in the same sector in the same period and the same sector, but without financial problems, were selected as the control group for the sample of the study. 24 financial ratios of the companies were used as the input data of the research. Support Vector Machines (DMV), Artificial Neural Networks (ANN) and Multiple Discrimination Analysis (MDA) were chosen as methods. According to the results of the research, it was seen that Artificial Neural Networks (ANN) achieved higher classification accuracy than other models. Due to its ease of use and high classification accuracy, it is recommended that both researchers and investors use Artificial Neural Networks (ANN) models.

Keywords: *Financial Failure, Bankruptcies, Financial Modeling, Support Vector Machines, Artificial Neural Networks.*

MAKİNE ÖĞRENME YÖNTEMLERİYLE KURUMSAL İFLASLARIN TAHMİN EDİLMESİ: ABD ÖRNEĞİ

ÖZET

Şirket iflaslarının önceden tahmin edilebilmesi şirket ortaklarını, yatırımcılarını, şirket alacaklılarını ve bu sektördeki diğer firmaların devamlılığını korumak için önemlidir. Doğru iflas tahminleri sayesinde şirket yöneticileri gerekli tedbirleri önceden alarak şirket iflaslarını önleyebilir ve yatırımcılar da zararlarını sınırlandırabilir. Bu çalışmanın amacı, makine öğrenmesi yapan yöntemler ile klasik sınıflandırma yapan yöntemlerin iflas tahmin performanslarının kıyaslanması ve sağlık sektöründeki iflasları önceden tahmin edebilen modellerin oluşturulmasıdır. Çalışmamın örneklemi için, ABD'de 01.01.2011 ile 31.12.2021 tarihleri arasında sağlık sektöründe bulunan 103 adet iflasını açıklayan şirket ve kontrol grubu olarak da aynı dönemde ve aynı sektörde bulunan fakat finansal bir sıkıntısı bulunmayan 103 adet şirket seçilmiştir. Bu firmalara ait olan 24 adet finansal oran, araştırmanın girdi verisi olarak kullanılmıştır. Destek vektör makineleri (DMV), yapay sinir ağları (YSA) ve çoklu ayırma analizi (MDA) yöntem olarak seçilmiştir. Araştırmanın sonuçlarına göre, yapay sinir ağları (YSA) diğer modellere oranla daha yüksek sınıflandırma başarısı elde ettiği görülmüştür. Kullanım kolaylığı ve yüksek sınıflandırma başarıların yüzünden hem araştırmacıların hem de yatırımcıların Yapay Sinir Ağları (ANN) modelleri kullanılmaları tavsiye edilmektedir.

Anahtar Kelimeler: *Finansal Başarısızlık, İflaslar, Finansal Modelleme, Destek Vektör Makineleri, Yapay Sinir Ağları.*

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1. Introduction

Bankruptcy prediction has been one of the areas of interest to many researchers, especially in the last 50 years and many bankruptcy prediction models have been put forward on this subject. Since the groundbreaking bankruptcy prediction model was introduced by Altman in 1968, many researchers have focused on predicting corporate financial distress. While many of these researchers distinguish between successful and unsuccessful companies; they have tended to use it as a dividing line, describing bankruptcy as a "final failure" (Shi & Li, 2019). One of the biggest disagreements about financial failure is the definition of companies as failures or in financial distress. While some authors use the term bankruptcy when describing financial distress, some authors define it as the liquidation or significant structural changes in the company (Muller et al., 2009). Min & Lee (2005) considered bankruptcy only as a criterion for financial failure, but financial failure is a long-lasting dynamic process.

Bankruptcy comes from the Arabic word "fulus". Fulus means that the resource is completely exhausted, even a coin is needed. Bankruptcy is when individuals and institutions borrow large amounts of money, fall into a liquidity shortage, and become unable to pay their debts (Demir & Teker, 2019). Bankruptcy is a state of failure for businesses, and it refers to the failure of businesses to pay their debts, difficulty in paying, delaying their payment, and consequently the loss of reputation and market share that will be encountered in the market. The continuation of the liquidity shortage along with financial failure is defined as bankruptcy as well (Aydın et al., 2010).

According to Altman & Hotchkiss (2006), legal action must be taken when a company fails to meet its debt servicing obligations. This is where bankruptcy occurs and is defined in two ways: In the first definition, bankruptcy is technically a firm's net worth position obtained by subtracting its liabilities from its assets. In the second, observable definition, bankruptcy is when a company makes a formal declaration to liquidate its assets or initiate a recovery program with a petition. According to Ross et al. (1999), there are three types of bankruptcy: The first is legal bankruptcy, which means the company goes to court to declare bankruptcy. The second is technical bankruptcy, which describes the inability of a company to repay the principal and interest within the contractual time. The third is accounting bankruptcy, which refers to a situation where a company only shows negative net book assets.

Bankruptcy, which is one of the consequences of financial failure, is the situation in which companies cannot fulfil their obligations by experiencing a liquidity squeeze rather than being unable to pay their debts. In practice, companies do not go bankrupt because of their debt. They go bankrupt because of a liquidity crunch.

The precise definition of financial failure or distress has yet to be determined but in terms of theoretical analysis, there are different degrees of financial distress. For example, the mildest financial failure can be characterized as a temporary cash crunch (Bruynseels & Willekens, 2012). The most serious financial failure is bankruptcy. According to another explanation, financial success and failure are classified according to the financial stress levels that affect companies. The level of financial stress can be estimated based on the total equity of the companies and how much liquidity generating power they have. This ratio indicates whether the company's financial stress is severe or mild.

If the financial stress experienced by the company is severe, this can lead to bankruptcy. Although financial failure and bankruptcy are used as synonyms in some studies, bankruptcy is the last resort to eliminate financial failure (Kınay, 2010). Determining whether companies fail financially or go bankrupt is important in terms of their market value and reputation. However, the company's financial failure does not mean that it will go bankrupt (Aktaş, 1997).

In the U.S., there are bankruptcy laws that allow financially troubled businesses to continue by liquidating their assets or making a fresh start with an arranged repayment plan so that they can pay off their debts. When we look at the basis of enterprises, in the bankruptcy applications of enterprises, the laws on liquidation are defined in the context of Chapter 7, while the laws on restructuring are regulated in the context of Chapter 11. Chapter 7 allows the sale of a debtor's non-exempt assets and the confiscation of their income. It then allows these proceeds to be distributed (liquidation) to corporate creditors under the provisions of the bankruptcy law (U.S. Courts, Chapter 7 Bankruptcy Basics). Chapter 11 of the bankruptcy law provides a new restructuring plan for companies or their partners. With this plan, companies have the opportunity to keep their business alive and pay off their debts to their creditors. Lawsuits filed under this article are considered as restructuring bankruptcy. Under Chapter 11, the debtor has the powers and duties of a trustee. During this period, it can remain in its possession, continue to run its business, and borrow money with court approval. (U.S Courts, Chapter 11 Bankruptcy Basics).

The Covid-19 pandemic has disrupted the functioning of daily life. It triggered a major economic slowdown all over the world, causing dramatic decreases in consumer spending and the inability of businesses to operate fully and effectively. This situation has sharply triggered the bankruptcy of commercial organizations (Grima et al., 2020; Khan et al., 2020), and corporate bankruptcies have once again become one of the current issues on a global scale.

As in many industries around the world, many international hospitals and healthcare institutions have faced serious financial difficulties related to the Covid-19 outbreak. In Kaufman Hall's 2021 year-end report for the American Hospital Association, it was emphasized that national hospitals in the USA suffered a net income loss of 54 billion dollars. In this report, it is predicted that the net income losses of hospitals will most likely be more profound in 2022. This foresight is due to three main reasons:

First, there has been a sharp increase in cases of emergencies requiring longer hospital stays than before the outbreak in 2019. Second, a decrease was observed in outpatients. The treatment costs of inpatients have higher expenses and lower profit margins than the costs of outpatients. Finally, there have been large increases in overall spending due to rising costs such as labour, medicines, services purchased, and personal protective equipment. Considering all these factors, it is thought that in 2022, there will be more bankruptcy cases, especially in the health sector. The Covid-19 outbreak reminded humanity of the importance that should be given to health and health services. In this sense, it is important to determine the risks of the administrative and financial failure of health institutions in advance for the protection and continuation of human life and to take the necessary precautions.

Financial distress is one of the most important threats faced by companies, regardless of their size and activities (Charitou et al., 2004). The financial failure of an enterprise causes the continuity of the operations of that enterprise and its stakeholders to suffer serious damage from this result (Sun et al., 2014). For this reason, the establishment of bankruptcy prediction models that give good and reliable results is of great importance in terms of the survival of the companies and the protection of the welfare levels of the stakeholders.

Altman (1968)'s model is a five-factor multivariate discriminant analysis (MDA) model. However, after Altman's study, other methods have often been used to develop different bankruptcy prediction models. Along with the discriminant analysis, logit analysis, probit analysis and artificial neural networks (ANN) are some of the commonly used methods (Gissel, 2007). Especially since the 1990s, neural networks have become one of the most widely used promising tools, as scientists have become more interested in artificial intelligence technology. ANN models have been used successfully in many financial problems, including bankruptcy prediction (Zhang et al., 1999). Applying this method, Tam & Kiang (1992), Altman et al. (1994), Wilson & Sharda (1994), Fletcher & Goss (1993), Lee et al. (1996) and Zhang et al. (1999) have had a great influence on subsequent research on the prediction of financial failure. In addition to this, Pan (2012) aimed to optimize the General Regression Neural Network model by applying the algorithm and obtained successful results showing the high rate of correct prediction ability of the model.

Understanding institutional failure presents an enormous theoretical challenge that must be met fundamentally because it is more about prediction than about explaining past efforts. Practical and commercial reasons cause failure prediction models to become more important for researchers, institutions and beneficiaries of these studies. (Etemadi et al., 2009). Studies using emerging technologies such as neural networks fall into the same design camp as previous studies and often use the same data in the literature, but use newer and more sophisticated techniques to distinguish firms with good results.

The first aim of this study is to compare the performances of machine learning methods and classical methods. In this context, the study aims to build three models that can predict bankruptcies in the health sector by using Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Multiple Discriminant Analysis (MDA)**.** In addition, this research aims to be a guided study for research done with SVM and ANN models. Because there are numerous advantages to using machine learning models to predict business bankruptcies.

Most of the studies dealing with company bankruptcies stand out as explanations rather than predictions, case studies, and studies focused on the process rather than the result. In the literature, there are studies on the use of machine learning models for the bankruptcy predictions of companies in different sectors. However, there are very few studies using machine learning models related to the health sector. It is thought that this study will contribute to the literature by applying the machine learning models to the health sector. It is claimed that the machine learning models discussed in the study are promising for bankruptcy predictions in the health sector.

Machine learning models (SVM, ANN etc.) do not need complicated equations and formulas like other classical bankruptcy prediction models. They build their algorithms (models) by doing machine learning from past data. Researchers and investors in similar industries and at different times can use these algorithms. In addition, models produced with machine learning methods can be programmed for continuous learning with an autonomous data flow. In this way, they can further improve their learning levels and increase their performance in accurately predicting bankruptcies. Artificial neural networks can overcome the effect of autocorrelation, which is often encountered in time series data and can tolerate problems, technical data errors, and missing values that are not taken into account in multiple regression models (Cybinski, 2001).

For this study, 103 companies in the health care sector in the USA, which declared bankruptcy between 2011 and 2021, and 103 companies that were financially successful in the same period were selected as a sample. Within the scope of this study, companies that declared bankruptcy under Chapter 11 were included in the research. The universe of the study is all companies operating in the health sector. The study is restricted to companies in the health care sector only, as companies in different sectors have different financial statement structures. As a result of the research, machine learning methods are expected to demonstrate high prediction performance.

2. Conceptual Framework

There are many studies in the literature using ANNs to predict financial failures. In most of the studies on ANN, ANN is compared with the MDA failure prediction model (Odom & Sharda, 1990; Koster et al., 1990; Cadden, 1991; Coates & Fant, 1992; Lee et al., 1996).

Odom & Sharda (1990) use ANNs for the first time to predict bankruptcy. They used the same financial ratios used by Altman (1968) and applied Artificial Neural Networks to a sample of active and bankrupt companies. In their research, three-layer feed-forward networks were adopted and the result was compared with the results of multivariate discriminant analysis. Between 1975 and 1982, 65 bankrupt firms and 64 non-bankrupt firms were taken as research samples. While the training set was created from these 74 firms (38 bankrupt and 36 non-bankrupt firms), the remaining 55 firms (27 bankrupt and bankrupt firms) constitute the training set. 28 companies that did not go bankrupt) were used to make the retention example. MDA was performed on the same training set as a benchmark. As a result, ANNs correctly classified 81.81% of the hand-held sample, while MDA only reached 74.28%. Fletcher & Goss (1993) compared the performance of ANN and logit regression models with data from 18 bankrupt and 18 financially successful firms in different industries. Using three variables of these firms, such as current ratio (CR), acid test ratio (QR), and income ratio (IR), the authors showed that they can make more accurate estimations with ANNs. Wilson (1994) conducted a study using ANNs with 5 financial ratios used in Altman (1968)'s model. He selected 65 bankrupted and 64 financially successful companies as sector and year matches. As a result of their studies, the researchers reached an accuracy level of 97%. Lee et al. (1996) developed three hybrid ANN models with the data of firms that went bankrupt between 1979 and 1992. They used 57 financial ratios belonging to Korean firms between 1979 and 1992. As a result of their studies, they obtained a successful ANN model that can predict 84% accurately among the three models. Davalos et al. (2005) created a genetic algorithm (GA) based ANN model to predict the financial distress and bankruptcy of airline companies. The authors used 21 financial ratios belonging to the financial statements of airline companies in the USA as a sample in their research. It has been observed that the model obtained as a result of the research has the success of estimating 94% correctly.

Various statistical methods have been used in other studies in the literature to define and measure the financial distress of companies in the health sector. Bazzoli & Andes (1995) defined hospitals with a "BBB" credit rating as financially distressed, based on a three-year average. Bond-rating valuations of hospitals are determined by external institutions such as Standard & Poor's and Moody's. However, the dates announced by these notes to the public may lag behind the actual financial difficulties or recovery processes of the hospitals. Therefore, the usefulness of credit notes is limited.

In 1996, Dimitras et. al extensively reviewed 47 published journal articles that developed failure prediction models between 1932 and 1994, revealing that discriminant analysis and logistic regression analysis methods were primarily used for failure prediction. However, in the following years, new methods started to be used, Ravi Kumar & Ravi (2007) presented a comprehensive survey of failure prediction studies published in the period 68-2005, also considering new methodologies. Ravi Kumar & Ravi (2007) also found that in most cases, the neural network approach outperforms statistical techniques when comparing traditional techniques such as discriminant analysis and logistic regression analysis, and artificial intelligence techniques such as neural networks. Jain & Nag (1997) expect ANN models to produce higher classification accuracy than models such as logistic regression because the primary purpose of ANNs is to provide satisfactory results in prediction support rather than parameter estimation or hypothesis testing.

Other studies in the literature have used companies' cash flows and profit margins to measure financial distress. However, cash flows and profit margins may not be considered the best measures of financial distress as they fail to capture the four areas of hospital finance (profitability, liquidity, solvency and asset efficiency) Financial Strength Index (FSI), created by Cleverly (1984), measures the financial health of a hospital in more than one area. This index is widely used as a measure of financial distress in hospitals. Richards (2014) confirmed the validity of the FSI with his study of hospital bankruptcies. Another method used to measure financial distress in hospitals is the Altman Z score. The Altman (1968) Z-Score was originally developed as a bankruptcy prediction model. However, it is still unclear whether the bankruptcy forecast differs from the financial distress forecast. Altman (1968) developed a multivariate bankruptcy model using the financial ratios of companies one year before the bankruptcy and tested it empirically. In his study, he built a bankruptcy prediction model by choosing 5 out of 22 financial ratios, using the multiple discriminant analysis (MDA) method for the period 1945-1965. These five financial ratios in the model; working capital / total assets, retained earnings / total assets, earnings before interest and taxes / total assets, the market value of equity / total liabilities and sales / total assets. With this model, Altman classified businesses as successful and unsuccessful with 95% accuracy up to one year before their bankruptcy and 72% accuracy up to two years before their bankruptcy.

Although other accounting-based financial distress forecasting models are widely used in various industries, their use in the healthcare industry has been limited. Two other estimation models used to predict financial distress in hospitals are the Ohlson (1980) O score and Zmijewski (1984). Puro (2019) analyzed 53 American hospitals that filed for bankruptcy and 53 financially stable American hospitals between 2006 and 2017 using the modified Altman Z score (1993), Ohlson (1980) and Zmijewski (1984) model. The authors concluded that a single model is not sufficient to predict bankruptcies, as a result of the different results they obtained from the results of their studies.

Swicegood & Clark (2001) take the initiative to explore new forecasting model techniques and compare them with existing approaches. His work uses discriminant analysis, neural networks and professional human judgment methodologies to predict the underperformance of commercial banks in the banking industry. Their results show that the ANN model shows slightly better predictive ability than other methods, but their predictions are necessarily limited to the banking sector (Omar et al., 2017). On the other hand, Akkaya et al. (2009) developed an artificial neural network model in their study to predict the financial failures of 52 businesses operating in the ISE (İMKB) during the 1998-2007 period in the textile, chemistry, oil and plastics sectors one year in advance. According to the financial failure criteria; Bankruptcy, exit from the stock market, cessation of operations, loss of 3 years or more, 28 successful and 24 unsuccessful businesses were identified, and these businesses were analyzed by dividing the data set into three as training, verification and test data. As a result of the analysis, the accuracy rate of the prediction was determined as 81%.

Many studies in different sectors also reveal that the predictive ability of ANNs to distinguish between failed and non-failed firms can produce predictive results comparable to traditional models (Lacher et al., 1995; Etheridge et al., 2000; Bloom, 2004; Sirakaya et al., 2005; Wu et al., 2006; Youn & Zheng, 2010).

Geng et al. (2015), concluded that ANN performance was not affected by variable selection, since the prediction accuracy of ANN models did not change significantly before and after variable selection. They also observed that the classification performance of ANN was higher than the classification accuracy of DT and SVM. Le & Viviani (2018) tried to predict the financial failure of 3000 US banks, including 1438 failures and 1562 successful runs. Two traditional statistical methods such as discriminant analysis and logistic theorem and three machine learning methods such as ANN, SVM and k-nearest neighbours were used as methods. For each bank, 5 years of data were collected. They observed that machine learning, ANN and kNN methods performed more effectively than traditional methods. ANN and the nearest neighbour algorithm proved extremely successful in accurately detecting financial failure, but they noted that failure was low in other methods. The empirical result shows that the ANN and nearest neighbour methods are the most accurate. In their study, Yürük & Ekşi (2019) used the data of 140 enterprises in the manufacturing sector traded on the BIST between 2008 and 2016. As a financial failure criterion; They have accepted the condition of losing 10% of their assets for 2 consecutive years. They compared the prediction performances of Artificial Neural Networks and Support Vector Machine (SVM) models. The performance of the model was tested by calculating the area under the curve by ROC analysis. In test data, ANN showed 79.66% and SVM 72.88% prediction accuracy in (t-1) year.

In the 2000s, many studies focused on metaheuristic algorithms for educating neural networks for binary classification problems like bankruptcy prediction (Wu et al., 2015; Ghasemiyeh et al., 2017; Alnaqi et al., 2019).

Pendharkar & Rodger (2004), suggested using a Genetic Algorithm (GA) grounded artificial neural network (GA-ANN) to master the relation weights for allocation problems. PSO-

BP algorithm, developed by Zhang et al. (2007), is a hybrid method that combines the PSO (particle swarm optimization) and backpropagation algorithms. According to Blum & Roli (2008), designing hybrid operations research and artificial intelligence methodologies becomes a common trend. As hybrids are designed to capitalize on synergies, the complementing traits of diverse optimization approaches are the main inspiration for the hybridization of various algorithms. Kiranyaz et al. (2009) adduced a multi-dimensional particle swarm optimization (MDPSO) method to make an ANN ready to come through the difficulties of current methods. Recent research, however, has found a lot of support for combining processes from several search strategies. In more recent works, Sarangi et al. (2013) introduced the DE-BP method, a hybridized DE (Differential Evolution) model with a backpropagation algorithm. By combining the strong local searching skills of the backpropagation algorithm with the global searching qualities of the DE evolutionary algorithm, the hybrid algorithm was used to educate the weights of the FFNN (Feedforward Neural Network) network. Georgescu (2016) propounded that metaheuristic approaches have proven to be better and easier to implement than gradient-based algorithms.

Today days, machine learning techniques are frequently employed to forecast bankruptcy. Support Vector Machines (SVM), ANN, Gaussian Process (GP), Classification and Regression Tree (CART), Logistic Regression (Logit), Decision Tree (DT), Random Forest (RF), Linear Discriminant Analysis (LDA), and ensemble learning approaches are some of the most widely used algorithms (Ansari et al., 2020). Shafiee et al. (2021) compared vector machine algorithms and artificial neural network (ANN) methods to predict company bankruptcies. They analysed 169 companies listed on the Tehran Stock Exchange between 2011 and 2019. 118 of these companies did not go bankrupt and 51 of them declared bankruptcy. According to the results of the research, the authors found that support vector machine algorithms have higher accuracy than artificial neural networks in predicting the bankruptcy of companies. Ptak-Chmielewska (2021) compared linear discriminant analysis (LDA) and Support Vector Machines (SVM) methods in his study. The author used data from 806 Polish companies in his study. 311 are companies that have declared bankruptcy, and the remaining 495 are in a good condition. At the end of the author's research, the author stated that the overall accuracy of the SVM was higher than LDA. Thilakaratna et al. (2022) used 10 years of financial data from more than 14,000 Irish and British companies in their study. They used the 29 new financial ratios that had never been used for forecasting bankruptcy before. As the result of the research, they success to improve a novel deep neural network model which has a high accuracy rate.

3. Data & Methodology

3.1. Data

Firms operating in the health sector in the USA are classified into three sub-sectors: hospitals, biotechnology & pharmaceuticals, and service manufacturers. Companies from these three sectors were included in the sample of the research. Between 01.01.2010 and 31.12.2021 in the USA, it was observed that 21.474 companies were working in the health sector. In the same period, 178 healthcare companies declared bankruptcy under Chapter 11 of the US Federal Bankruptcy Code. All of the financial data of 103 of these 178 companies could be accessed. The number of companies in the group (1) and group (2) is arranged to be equal (Altman, 1968:

593). Group (2) (control group) was selected among companies that were actively involved in the health sector in the USA between 2011 and 2021 and had no financial difficulties.

Table 1: Descriptive Statistics

Model	N	Minimum (Million $)	Maximum (Million $)	Mean (Million $)	Std. Deviation (Million $)
Bankrupt (Group1)	103	0.001	68,012	2,758	8,748
Non-bankrupt (Group 2)	103	0.240	1,485	371	323

As can be seen in Table 1, the asset sizes of these 103 companies (group 1), which declared bankruptcy, are between $ 0.001 million and $ 68,012 million, with an average of $ 2,758 million. The 103 financially successful companies (group 2) have assets between $0.240 million and $1,485 million with an average of $371 million. As in the studies of Altman (1968), Cho (1994) and Gu et al. (2000), in this study, the ratios of the financial statements announced by the companies 1 year before the bankruptcy were used to estimate the classification model.

After the companies are selected for the sample, the most important issue is the selection of the financial ratios to be used in the analysis. Financial ratios should be those that best reflect the financial conditions and performance of healthcare companies. In this study, 24 financial ratios are grouped under 5 main headings.

Table 2: Financial Ratios Selected for the Sample of the Study

Code[1]	Financial Ratios	Formula
	Liquidity Ratios	
X_1	Current Ratio	Current Assets / Current Liabilities
X_2	Liquid (Acid-test) Ratio	(Current Assets- Inventories) / Current Liabilities
X_3	Cash Ratio	Cash and Cash Equivalents / Current Liabilities
	Financial Structure Ratios	
X_4	Debt to Equity Ratio	Total Liabilities / Total Equity
X_5	The Current to Total Liabilities Ratio	Current Liabilities / Total Liabilities
X_6	Equity to Fixed Assets Ratio	Equity / Fixed Assets
X_7	Interest Coverage Ratio	EBIT /Interest Expenses
	Operating Turnover Rates	
X_8	Asset Turnover Rate	Net Sales / Average Total Assets
X_9	Equity Turnover Rate	Net Sales / Average Shareholders' Equity
X_{10}	Fixed Asset Turnover Ratio	Net Sales / (Gross fixed assets - Accumulated depreciation)

1 In the next stages of the study, the financial ratios will be expressed with the short codes shown in Table 2 and Table 3 so that the reader can easily follow them.

Table 2 continue

X_{11}	Current Asset Turnover	Net Sales / *Average Current Assets*
	Profitability Ratios	
X_{12}	Gross Margin	Gross Profit / Net Sales
X_{13}	Operating Profit Margin	Operating Profit / Net Sales
X_{14}	Net Profit Margin	Net Profit / Net Sales
X_{15}	Return On Equity	Net Profit / Equity
X_{16}	Return On Assets	Net Profit / Total Assets
X_{17}	EBIT/Total Assets	EBIT/Total Assets

Source: Author's compilation

As can be seen in Table 2, the four groups consist of business-specific financial ratios and variables related to corporate governance.

Table 3: Financial Ratios Selected for the Sample of the Study

Ratios Commonly Used in Bankruptcy Models in the Literature			
Code	**Reference Model**	**The Coefficient in the Model**[2]	**Formula**
X_{18}	Altman Model (1968) Springate Model (1978) Fulmer Model (1984) Ohlson Model (1980) Grover Model (2001)	*Z1* *S1* *F8* *O3* *G1*	Working Capital / Total Assets
X_{19}	Springate Model (1978)	*S3*	EBT / Current Liabilities
X_{20}	Fulmer Model (1984)	*F3*	EBT / Total Equity
X_{21}	Altman Model (1968)	*Z4*	Market Value of Equity / Total Liabilities
X_{22}	Ohlson Model (1980)	*O6*	Cash Flows From Operation / Total Liabilities
X_{23}	Altman Model (1968) Fulmer Model (1984)	*Z2* *F1*	Retained Earnings / Total Assets
X_{24}	Fulmer Model (1984)	*F5*	Total Liabilities / Total Assets

Source: Author's compilation

Beaver (1966) selected the independent variables to predict financial failure based on their popularity in the literature and their prediction success in previous research (Garcia Gallego et al., 2021). Therefore, as seen in Table 3, the 5th group has been chosen from among the financial ratios frequently used in the literature.

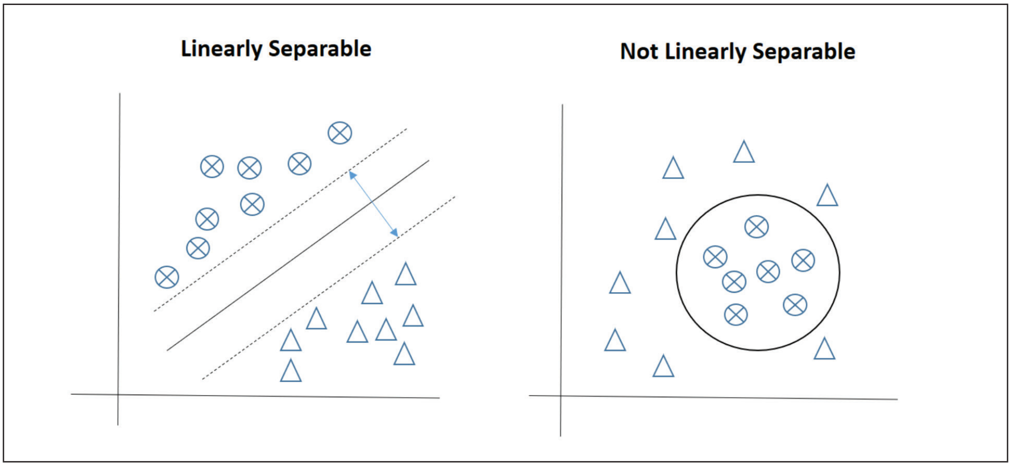
2 The model coefficient column shows the coefficient number of the variable in the reference model.

3.2. Methodology

3.2.1. Support Vector Machine (SVM) Model

Support Vector Machines (SVM) is one of the simple machine learning methods commonly used in classification problems. SVMs using a sigmoid kernel function are built on a feed-forward and two-layer artificial neural network (Haykın, 1999).

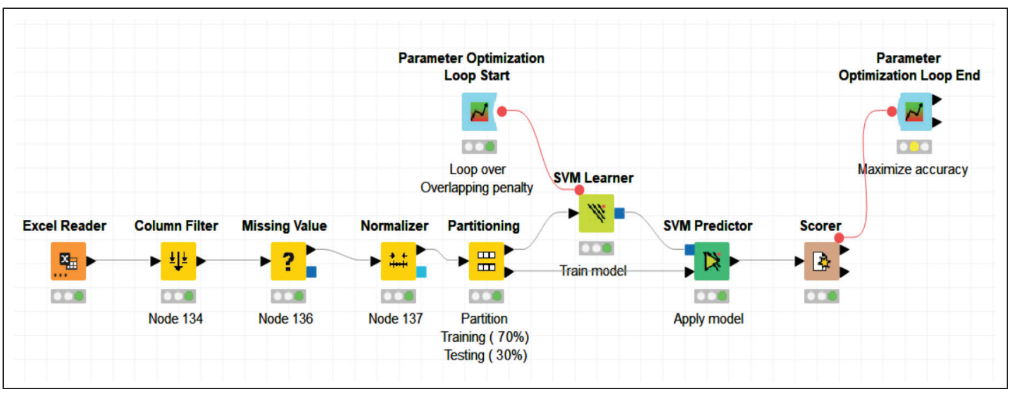
Figure 1: Linearly Separable Data and Non-Linearly Separable Data



Source: Author's compilation

As can be seen in Figure 1, SVMs can make classifications for linear and nonlinear data[3].

Figure 2: Application of Artificial Neural Network Models Made on Knime Program



Source: Author's compilation

3 It uses Kernelized SVM for non-linearly separable data.

Figure 2 shows the topology of the SVM model developed with the help of the Knime program. In the model, the input data is entered into the system with the help of the “Excel Reader” node. The data used in the model are filtered with the “Column Filter” node (Özparlak, 2021). Extremely large or small values in the input data entered into the SVM model may mislead the network. Thanks to normalization, all values in the data set are normalized and extreme values are prevented from misdirecting the network (Yavuz & Deveci 2012: 175). In the Knime program, the normalization of the data was done with the help of the “Normalizer” node. In addition, the min-max normalization method was used to fit the data to the normal distribution.

$$X' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

In the normalization formula shown in Equation 1, X' =normalized data, X_i =input data, $X_{\min}$ =the smallest value in the input data, $X_{\max}$ =the largest value in the input data. In this study, 70% of the SVM data is reserved for machine learning and 30% for testing with the help of the “Partitioning” node.

“Parameter Optimization Loop Start” and “Parameter Optimization Loop End” nodes are used for network optimization. With the help of these two nodes, the best parameter is provided. The expected output values are calculated with the help of the “SVM Predictor” node. The correct and incorrect classifications matrix, the success rate of the SVM model, the error rate and Cohen’s Kappa Coefficient ***(K)*** were calculated with the “Scorer” node. Cohen’s Kappa Coefficient is a statistical method that measures the degree of agreement between two observers who evaluate at the classification level (Cohen, 1960:37). Cohen’s Kappa Coefficient is used to measure the degree of agreement between training data and test data in ANN models.

$$\varkappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \tag{2}$$

In Equation 2, *Pr(a)* shows the sum ratio of the observed fit for the two raters of the results obtained as a result of the SVMs. *Pr(e)* denotes the probability of this fit occurring by chance. $\varkappa$ value shows Cohen’s Kappa Coefficient obtained as a result of the formula (Özparlak, 2021).

Table 4: Interpretation of Cohen’s Kappa Coefficient

Kappa Coefficient	Interpretation
<0.00	No Agreement
0.00-0.20	None To Slight
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Substantial
0.81-1.00	Almost Perfect Agreement

Source: Landis, J. R. & Koch, G. G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33, 159-174.

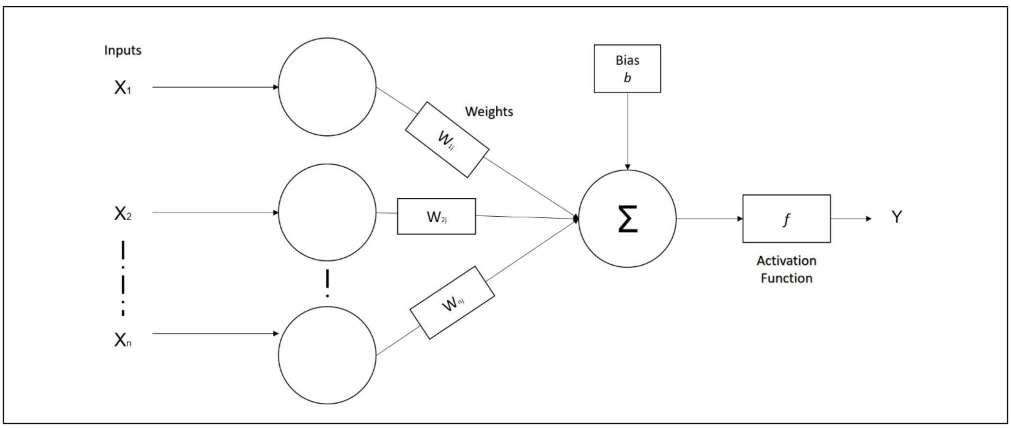
Table 4 shows the table used to interpret Cohen's Kappa Coefficient (Landis & Koch, 1977:165).

3.2.2. Artificial Neural Networks (ANN) Model

With the latest developments in technology, artificial neural networks (ANN) have been used frequently by researchers because ANNs are systems that can learn about events, make logical decisions in the face of similar events, and produce information about previously unseen examples. ANNs can make generalizations from the examples (input and output values) given to them during their training, and they can generate information about new examples due to these generalizations (Özparlak, 2021).

In this study, it is expected that ANNs will build a highly accurate financial failure prediction model by learning from financial ratios and to be able to use the model for similar sectors in the future.

Figure 3: A Simple Modeling of Artificial Neural Networks



Source: Author's compilation.

Figure 3 shows a simple model of artificial neural networks.

$$Z_i = \sum_{i=1}^{n} (w_{ij} x_i + b) \tag{3}$$

Z_i value and summation function are presented here. The summation function is created by adding the bias (b) showing the experience obtained from the previous information to the sum of the data from the input layer, according to different weights.

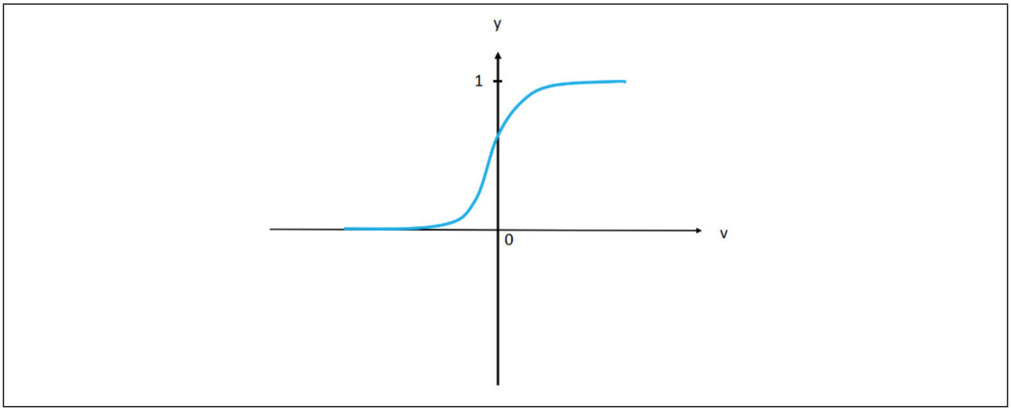
$$y = f(Z_i) = f\left(\sum_{i=1}^{n} (w_{ij} x_i + b)\right) \tag{4}$$

$f(Z_i)$: The activation function provides the matching between the input and output units. In this study, the sigmoid function, which is one of the most used activation functions in applications, is used.

$$S(x) = \frac{L}{1 + e^{-x}} = \frac{e^x}{e^x + 1} \tag{5}$$

In the formula in Equation 5, the mathematical definition of the sigmoid function is given.

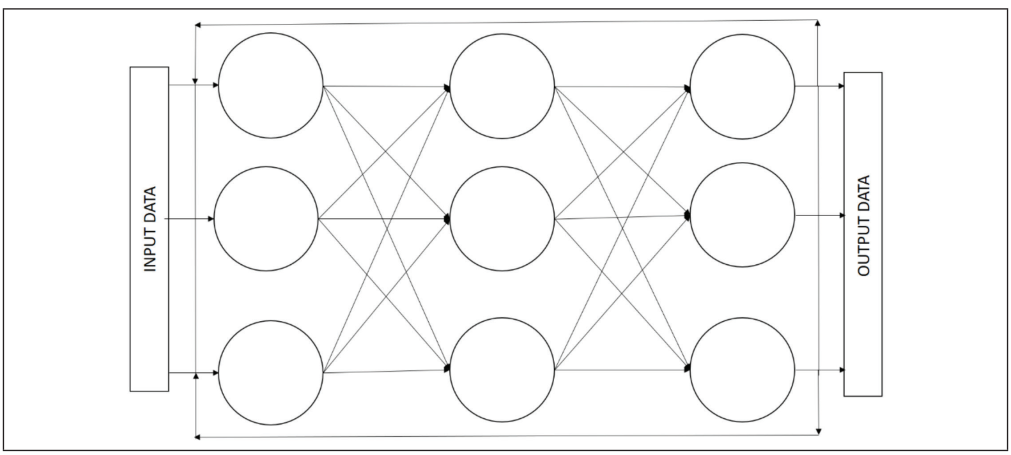
Figure 4: Sigmoid Function



Source: Author's compilation

As seen in Figure 4, the Sigmoid function always takes values between 0 and 1, so the activation value does not show extreme values. ANNs are divided into two "feed-forward" and "feedback" networks according to the flow direction of the cells. In feedforward networks, the direction of information flow only moves forward and towards the output layer. In feedback networks, the flow of information moves from the output units in the output and intermediate layers to the input units or previous intermediate layers, and back (Aşkın et al., 2013). Feed-forward networks are frequently used in applications. Multi-layered perception (MLP) networks are multi-layered and feed-forward networks trained with static back distribution (Kutlu & Badur, 2009). In this study, multilayer perception and feedforward network structure are used.

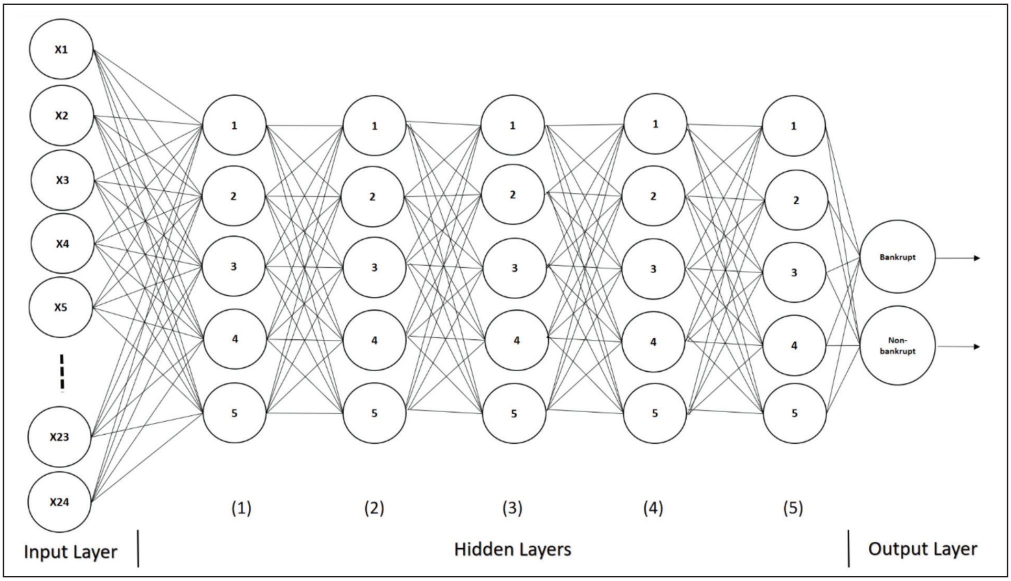
Figure 5: Structure of Feed Forward Network



Source: Author's compilation

Figure 5 shows the artificial neural network model used in the study.

Figure 6: Variables Used as Input and Output in Artificial Neural Network Analysis

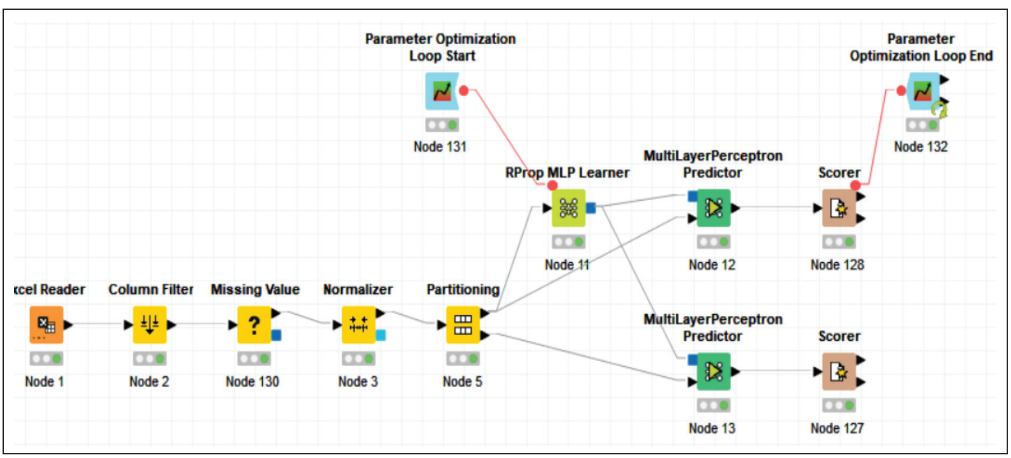


Source: Author’s compilation

As seen in Figure 6, the input layer of the model consists of 24 variables obtained from financial ratios. The output layer consists of the bankrupt group of companies (1) and the non-bankrupt group of companies (2).

In this study, the Knime package program was used to implement the ANN model.

Figure 7: Application of Artificial Neural Network Models Made on Knime Program



Source: Author’s compilation

Figure 7 shows the topology of the ANN model created with the help of the Knime program. In the model, the input data is entered into the system with the help of the "Excel Reader" node. The data used in the model are filtered with the "Column Filter" node (Özparlak, 2021). Extremely large or small values in the input data entered into the ANN model may mislead the network. Thanks to normalization, all values in the data set are normalized and extreme values are prevented from misdirecting the network (Yavuz & Deveci 2012:175). In the Knime program, the normalization of the data was done with the help of the "Normalizer" node. In addition, the min-max normalization method was used to fit the data to the normal distribution.

$$X' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{6}$$

In the normalization formula shown in Equation 6, X' =normalized data, X_i =input data, $X_{\min}$ =the smallest value in the input data, $X_{\max}$ =the largest value in the input data. In this study, 70% of the ANN data is reserved for machine learning and 30% for testing with the help of the "Partitioning" node. Multilayer perception (MLP) and feedforward network model is made with "RProp MLP" node.

"Parameter Optimization Loop Start" and "Parameter Optimization Loop End" nodes are used for network optimization. With the help of these two nodes, the best parameter is provided by entering 5 layers, 5 hidden neurons per layer, and 10.000 maximum iterations. The expected output values are calculated with the help of the "MultiLayerPerceptron Predictor" node. The correct and incorrect classifications matrix, the success rate of the ANN model, the error rate and Cohen's Kappa Coefficient ***(K)*** were calculated with the "Scorer" node (Özparlak, 2021). Cohen's Kappa Coefficient is a statistical method that measures the degree of agreement between two observers who evaluate at the classification level (Cohen, 1960:37). Cohen's Kappa Coefficient is used to measure the degree of agreement between training data and test data in ANN models (see equation 2 and table 4).

3.2.3. Multiple Discriminant Analysis (MDA)

Multiple Discriminant Analysis (MDA) is one of the methods widely used in the literature to distinguish between bankrupt and non-bankrupt firms. The Multiple Discriminant Analysis (MDA) method was first used by Altman (1968) to distinguish between bankrupt and non-bankrupt firms. After Altman's study, many bankruptcy prediction models using financial ratios have been developed.

There are 3 assumptions for the application of the multiple separation analysis (MDA) model (Altman & Narayanan, 1997).

1. *The data should have a normal distribution*
2. *There should be no multicollinearity problem between the variables*
3. *The covariance matrices should be equal*

4. Findings

4.1. Results of Support Vector Machine (SVM) Model

In this section, the results of the ANN models created according to the multi-layer and feed-forward network structure are given. 70% (144 items) of the data of the companies included in the research were used in the training set and 30% (62 items) in the test set.

Table 5: ANN Model Classification for the Training Set

	Bankrupt	Non-Bankrupt	
Bankrupt	24	6*	
Non-Bankrupt	7**	25	
Correct Classified	49	**Wrong Classified**	13
Accuracy	79.03%	**Error**	20.97%
Cohen's Kappa Coefficient (K)	0.58		

** Type I Error **Type II Error*

Table 5 shows the performance results of the artificial neural network models created using the sample data of financially bankrupt and non-bankrupt companies. According to this table, the accuracy rate is 79.03% (49 items). The Error rate is 20.97% (13 items). Cohen's Kappa Coefficient shows a moderate agreement with a level of 0.58

4.2. Results of Artificial Neural Networks (ANN) Model

In this section, the results of the ANN models created according to the multi-layer and feed-forward network structure are given. 70% (144 items) of the data of the companies included in the research were used in the training set and 30% (62 items) in the test set.

Table 6: ANN Model Classification for the Training Set

	Bankrupt	Non-Bankrupt	
Bankrupt	0	1*	
Non-Bankrupt	15**	68	
Correct Classified	128	**Wrong Classified**	16
Accuracy	88.89%	**Error**	11.11%
Cohen's Kappa Coefficient (K)	0.779		

** Type I Error **Type II Error*

Table 6 shows the performance results of the artificial neural network models created using the training set data of financially successful and unsuccessful companies. According to this table, the accuracy rate is 88.89% (128 items). The Error rate is 11.11% (16 items). Cohen's Kappa Coefficient shows a substantial agreement with a level of 0.779.

Table 7: ANN Model Classification for Test Set

	Bankrupt	Non-Bankrupt	
Bankrupt	25	3*	
Non-Bankrupt	3**	31	
Correct Classified	56	**Wrong Classified**	6
Accuracy	90.33%	**Error**	9.67%
Cohen's Kappa Coefficient (K)	0.805		

** Type I Error **Type II Error*

Table 7 shows the performance results of artificial neural network models created using test set data of financially successful and unsuccessful companies. According to this table, the accuracy rate is 90.33% (56 items). The error rate is 9.67% (6 items). Cohen's Kappa Coefficient of 0.805 shows substantial agreement. The success rate of the model obtained from ANN was realized as 90.33%.

4.3. Multiple Discrimination Analysis (MDA) Model

It should not be forgotten that there are 3 assumptions for the application of the Multiple Discrimination Analysis (MDA) model.

1. The data should have a normal distribution (Dietrich et al., 1984; Ballard et al., 1988). For the data to fit the normal distribution, first of all, the vaccine endpoints were removed from the data set. The results of normality, Kurtosis and Skewness values of the data were calculated. After the normality of the data was ensured, whether the financial ratios changed in bankrupt and non-bankrupt companies was also measured with the help of the T-test. According to the results of the t-test, it was observed that the independent variables of X_1, X_2, X_3, X_4, X_7, X_9, X_{12}, X_{13}, X_{14}, X_{16}, X_{17}, X_{18}, X_{19}, X_{21}, X_{22} and X_{24} differed significantly at least at the level of 0.05. Other variables that did not comply with this condition were excluded from the sample.

2. There should be no multicollinearity problem between the variables (Mihalovič, 2016:105). The fact that the correlation between the variables is not higher than 0.80 is an indication that the independent variables may be suitable for discriminant analysis (Buyukozturk, 2006). There is no variable which is higher than 0.80 in the sample.

*3. The covariance matrices should be equal (*Wieprow et al., 2021; Ohloson, 1980:112). In this study, since the covariance matrices are not equal to each other, the covariance matrices were made according to the separate group option and the results were obtained accordingly. (Box's M *p value*=.685)

As a result of the discriminant analysis, the Eigenvalue value was found to be 0.564 and the Wilks' Lambda value to be 0.639.

$$Z_i = .709 * X_{18} + .290 * X_{12} + .273 * X7 + .56 \,.\, X_{13} \tag{7}$$

As a result of the discriminant analysis, the result in equation (7) was reached. In this model,

$X_{18:}$ represents the Working Capital / Total Assets variable.

X_{12}: Represents the Gross profit / Revenue variable.

X_7: Represents the EBIT / Interest Expenses variable.

X_{13}: Represents the Operating Income / Revenue

It has been concluded that the X_{18}, X_{12}, X_7 and X_{13} variables are important for detecting financial failures in the health care sector. The accuracy rate of the function created as a result of the discriminant analysis was calculated at the level of 82.0%.

5. Conclusion

Forecasting bankruptcy has been one of the areas of interest to many researchers, especially in the last 50 years. Many international hospitals and healthcare institutions have faced serious financial difficulties related to the Covid-19 pandemic. It is thought that in 2022, there will be more bankruptcy cases, especially in the health sector. Being able to predict company bankruptcies is important to protect company partners, investors and company creditors. In this way, company managers can prevent bankruptcy by taking the necessary precautions, and investors can limit their losses.

The first aim of this study is to compare the performances of machine learning methods and classical methods. Second aims to build three models that can predict bankruptcies in the health sector by using Support Vector Machine (SVM), Artificial neural networks (ANN) and Multiple Discrimination Analysis (MDA) methods. In addition, this research aims to be a guided study for ANN models.

For the sample of this study, 103 companies in the health sector that declared bankruptcy between 01.01.2011 and 31.12.2021 in the USA and 103 companies that were in the same sector and the same period but had no financial problems were selected as the control group. 24 financial ratios belonging to these companies were used as input data. SVM, ANN and MDA were chosen as the method in the study. According to the results of the research, the accuracy rate of the SVM models was 79.03%. In other literature studies on the prediction of financial failures with SVMs, Yürük et al. (2019) 72.88%, Shafiee et al. (2021) approximately 88.8%, Ptak-Chmielewska (2021) 72.1%. According to the results of the research, the accuracy rate of the artificial neural network models developed using the training set data of the model obtained by ANN is 88.89%. The accuracy rate of artificial neural network models created using test set data is 90.33%. In other literature studies on the prediction of financial failures with ANNs, Wilson (1994) found 97%; Lee et al. (1996) 84%; Davalos (2005) achieved 94%, Yürük et.al (2019) 79.66%, Shafiee et al. (2021) approximately 92%, Thilakarathna et al. (2022) approximately 84.55%. In this sense, the correct classification rate obtained with this study is at a reasonable level. In addition, the accuracy rate of the model made with a classical bankruptcy prediction method (Multiple Discriminant Analysis) is 82.0%. As a result, accuracy classification increased by 6.89% with financial forecasting models made with artificial neural networks.

Moreover, the implementation of classical models is quite troublesome. For MDA models to be valid, they must meet the conditions such as normality, significance, no multicollinearity problems and equal covariance matrices. In this study, too many variables had to be excluded from the sample to meet the conditions. This resulted in missing data. In addition, the accuracy of the estimation of classical models such as the multiple discriminant analysis (MDA) method is significantly reduced when the model is used in another industry, at another date, or in a commercial setting different from the data used to derive the model (Wu et al., 2010; Grice et al., 2001; Pitrova, 2011; Wieprow et al., 2021). This means that models must be constantly updated in order to make successful models of financial failure. This greatly increases the workload on both researchers and investors. On the other hand, ANNs can be easily used in similar industries, thanks to their ease of application, the need for no model, and their high classification performance.

According to the results of this research, ANNs are promising in the field of predicting company bankruptcies with their high classification success and ease of use. Thanks to the ANN method and applications learned from this study, researchers can be advised to predict the bankruptcy of companies in other sectors or countries with a high risk of bankruptcy. With the machine learning models, it is also possible to predict the financial failures of businesses in different sectors. For examples, the manufacturing industry, the energy industry, the automotive industry, the transport and logistics industry, and the service industry.

Machine learning methods are promising with their superior classification capabilities. Therefore, it is recommended for researchers to conduct studies in which more machine learning methods are compared in different sectors in their future studies.

Conflict of Interest

The authors declare that they have no conflict of interest.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors. The research and publication ethics were considered when preparing the article.

Contribution Rates

All authors have contributed equally in diverse stages of the article.

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