COMPARISON OF CLASSIFICATION PERFORMANCE OF MACHINE LEARNING METHODS IN PREDICTION FINANCIAL FAILURE: EVIDENCE FROM BORSA İSTANBUL*

Barış AKSOY[1]
Derviş BOZTOSUN[2]

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Abstract: This study aimed to predict the 1 to 2 year future time of the financial failure of 86 manufacturing companies that are operating in Borsa İstanbul. The data comprised of 2010-2012 period, and it depends on 8 quantitative financial variables. Beside 6 variables come from non financial statements. In the study, Artificial Neural Network (NN), Classification and Regression Trees (CART), Support Vector Machine (SVM) and k-Nearest Neighbors (KNN) were used to compare classification performances of related methods. ROC Curve was used to compare the classification performance of the methods. As a result of the analyseis, the overall classification accuracy from the highest to the lowest was SVM (92,31%), CART (88,46%), ANN (84,62%) and KNN (80,77%) 2 years before the financial failure. The overall classification accuracy from the highest to the lowest was CART (96,15%), ANN (92,31%), SVM (80,77%) and KNN (84,62%) 1 year before the financial failure. Return on Equity (ROE) and Return on Assets Ratio (ROA) were found as important variables in the creation of the CART decision tree. The fact that the four models obtained in thise study predicted financial success/failure at a higher rate, and it shows that the models obtained in this study can be included in the models used by relevant people.

Keywords: *Financial Failure Prediction, Borsa Istanbul, Artificial Neural Networks, Classification and Regression Trees, Support Vector Machine*

Finansal Başarısızlık Tahmininde Makine Öğrenmesi Yöntemlerinin Sınıflandırma Performansının Karşılaştırılması: Borsa İstanbul Örneği

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Özet: Bu çalışmada Borsa İstanbul İmalat Sanayi Sektörüne kayıtlı 86 firmanın, 2010-2012 dönemine ait verileri kullanılarak 1 ve 2 yıl öncesinden finansal başarısızlık tahmini yapılmıştır. Araştırmada 8 mali tablolara dayalı nicel ve 6 mali tablolara dayalı olmayan değişken kullanılmıştır. Çalışma amacına yönelik analizlerde Yapay Sinir Ağları (ANN), Sınıflandırma ve Regresyon Ağaçları (CART), Destek Vektör Makineleri (SVM) ve K-En Yakın Komşular Algoritması (KNN) yöntemlerinin tahmin performansları yöntemlerin ayırt edici özellikleri altında karşılaştırılmıştır. ROC Eğrisi yöntemlerin sınıflandırma performanslarını karşılaştırmak için kullanılmıştır. Analiz sonucunda, finansal

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[1] Corresponding Author, Asst. Prof. Dr., Sivas Cumhuriyet University, Faculty of Economics and Administrative Sciences, Department of Finance and Banking, Sivas, Turkey. baksoy@cumhuriyet.edu.tr, https://orcid.org/0000-0002-1090-5693
[2] Prof. Dr., Kayseri University, Faculty of Applied Sciences, Management of Accounting and Finance, Kayseri, Turkey. dboztosun@kayseri.edu.tr, https://orcid.org/ 0000-0002-2656-2701

başarısızlıktan iki yıl önce en yüksekten düşüğe genel sınıflandırma doğruluğu SVM (% 92,31), CART (%88,46), ANN (% 84,62), KNN (%80,77) olarak bulunmuştur. Finansal başarısızlıktan bir yıl önce en yüksekten en düşüğe genel sınıflandırma doğruluğu CART (% 96,15), ANN (%92,31), SVM (% 80,77) ve KNN (%84,62) olarak elde edilmiştir. CART karar ağacının oluşturulmasında önemli değişkenler olarak Özsermaye kârlılığı (ROE) ve Aktif Kârlılık Oranı (ROA) bulunmuştur. Çalışmada elde edilen dört modelin finansal başarı/başarısızlığı bir ve iki yıl öncesinden yüksek oranda tahmin etmesi, ilgililerin kullandıkları modeller içerisine bu çalışmada elde edilen modelleri dâhil edebileceklerini göstermektedir.

Anahtar Kelimeler: *Finansal Başarısızlık Tahmini, Borsa Istanbul, Yapay Sinir Ağları, Sınıflandırma ve Regresyon Ağaçları, Destek Vektör Makinesi*

1. INTRODUCTION

Failure in businesses has a negative impact almost on all countries at different levels depending on the number and size of failing businesses of countries. The number of failing businesses is accepted as an indicator of the development and robustness of the economy. The prediction of financial failure due to the existence of high individual, economic and social costs in financial failure and bankruptcy cases in businesses provide an important opportunity to identify the failures in time and to take necessary measures for investors, creditors, lenders and governments (Etemadi et al., 2009, p.3199). Therefore, a large number of banks, creditors and investors develope models to assess the risk arising from loans or receivables. These models enable whether the money can be lend and decide on what conditions to lend, while allowing the interest rate to be assessed based on the expected risk of repayment (Jardin and Séverin, 2011, p.701). Business failure arises in two ways. They are economic and financial failures. The term business failure refers to the economic failure of businesses by excess of expenses over their revenues (Li and Sun, 2013, p.186). Financial failure occurs in the form of technical bankruptcy and bankruptcy. The technical bankruptcy is the condition of a business that is unable to make payment on a liability but its business assets are generally sufficient to pay the liabilities. The bankruptcy represents the situation where the business debts can not be covered by the business assets (Sayılgan and Ece, 2016, p.50).

A financially unsuccessful business may experience different situations between the temporary deterioration of cash flow and bankruptcy. Financial failure is a dynamic process, which is the result of a poor business run for months to years or even longer (Sun et al., 2014, p.43). It may be too late for investors to sell their share certificates, futures and option contracts, or to collect the receivables of creditors (Chen, 2011, p.11262). Therefore, in this study, prediction was made before 1 and 2 years, which is a period that can enable the concerned persons to take the necessary precautions before financial failure.

One of the biggest problem of businesses in financial failures is the disagreement on defining the company failure or financial distress. While defining the financial distress, some authors used the bankruptcy term. On the other hand, other authors described financial distress as liquidation or significant structural changes in the company (Muller et al., 2009, p.22). Many people confuse financial failure with concepts such as default, bankruptcy and liquidation, which have different meanings. Financial failure does not always result in bankruptcy (Bilir, 2015, p.9). In developing countries, all situations between businesses having difficulty in paying their overdue debts and bankruptcy are expressed as financial failure (Selimoğlu and Orhan, 2015, p.25). In this study, the definition of financial failure used in the study of Selimoğlu and

Orhan (2015) was adopted. Therefore, the financial failure criteria given in Table 1 were used in our study.

In this study, the importance of variable selection in the prediction of financial failure and the effects of the models structured with different variables on the classification power were determined. According to the financial ratios and non-financial criterias, 43 successful and 43 unsuccessful businesses that were registered in the Istanbul Stock Exchange (ISE; renamed Borsa Istanbul in January 2013) and operating in manufacturing industry were determined. Using the data of businesses from the 2010-2012 period, Classification and Regression Trees (CART), Support Vector Machine (SVM), k-Nearest Neighbors (KNN) and Artificial Neural Network (NN) analysis were used to compare classification performances of related methods. In terms of financial failure criteria used in this study between 2010 and 2015, the highest number of businesses failed in 2012. Therefore, 2012 was considered as a year of failure for financially unsuccessful businesses and as a successful year for financially successful businesses. Financial successful/unsuccessful businesses in 2012 were predicted by using the data of one year (2011) and two years (2010) before 2012.

The study differs from the literature in the following aspects:

In a study by Min and Lee (2005), the authors addressed the bankruptcy of the business as the only financial failure criteria. However, financial failure is a dynamic process that lasts from months to years or even longer. It can be said that the related business is a failure when a business encounters any of the situations such as bankruptcy, default of bonds, non-payment of debts in due date, requesting bankruptcy of the business, clearly declaring that debts cannot be paid, agreement with creditors to reduce debts (Sun et al., 2014, p.43). In this study, four financial failure indicators based on financial statements and one financial failure indicator not based on financial statements were used to identify successful and unsuccessful businesses.

The objectives of this study are:

✓ To determine the impact of the sample selected based on financial statements and non financial statements of success/failure criterias on financial failure prediction of performance
✓ To create a comprehensive set of variables with superior prediction ability by using the financial ratios obtained from financial statements and qualitative variables obtained from company news and announcements
✓ To develop models with high prediction accuracy, working in harmony with the predetermined variables in this study.
✓ To determine the methods and models with the highest prediction power of ANN, CART, SVM, KNN algorithm methods used in the study and compare the obtained models within the framework of their distinctive features and limitations.

The models created according to the research results can be used by natural and legal persons such as company managers, shareholders, suppliers, lenders, investors, potential investors, public institutions, users of financial statements, etc. to support existing prediction methods before important decisions are made. As a result of the use of the models obtained as a result of this research, effective management control and faster response to changing economic conditions will be ensured for businesses. Besides, the models created can be used in credit evaluation, assist investment decisions, be used as an auxiliary tool in independent external auditing, will be effective in determining the direction of monetary policies to be determined by the Central Bank, and in the formation of supervisory policies to be determined by regulatory and supervisory institutions such as the Banking Regulation and Supervision Agency and the CMB.

The relationship between the financial ratio and the state of the company can be dynamic, and the financial ratios can vary in various industries and in different stages of economic cycles. Therefore, following the study of Wu et al. (2006), it is not claimed in our study that the data set can be generalized. 8 quantitative variables and 6 qualitative variables obtained from the balance sheet and income statement have been used in the independent variables. The first part of the research presents the introduction section. The second part present the literature review, and the third is the methodology. The fourth, and fifth sections give the findings, and conclusion.

2. LITERATURE REVIEW

In the area of financial failure prediction, many models have been developed until today. The complexity of some of these models has made it impossible for users to clearly understand the internal mechanism of the technique and thus caused them not to use in their works. Therefore, they need simple financial failure models that contain the features of easy interpretation, clarification and comprehension (Sun et al., 2014, p.53). There are many studies in the literature on financial failure prediction, both at home and abroad. In order to limit the research content, studies in which at least one of the machine learning methods used, was included in the literature review.

Huang et al. (2004) used two different data sets including commercial banks in the US and financial institutions in Taiwan using Support Vector Machines (SVM) and Neural Network (NN) techniques. It was seen that the support vector machine obtained comparable accuracy with the neural networks. Classification and prediction accuracy were determined using the 10-fold cross validation method and classification accuracy was found to be SVM (79,73%)>NN (75,68%) in Taiwan I set, and SVM (77,03%)>NN (75,68%) in Taiwan II data set, respectively. Classification accuracy was found to be NN (80,00%)> SVM (78,87%) in the US I data set and SVM (80,00%)> NN (79,25%) in the US II data set.

Min and Lee (2005) used Support Vector Machine (SVM) and Neural Networks (NN) techniques to predict financial failure. A bankruptcy prediction model with high prediction power was created by using 5-fold cross validation methods and selecting parameter values in order to select the upper limit C and optimal kernel parameter values for SVM model selection. According to the results of the empirical analysis, it was reported that SVM performed better than other methods. According to the analysis in which they examined 38 financial ratios, the classification accuracy was found to be SVM (83,06%)> NN (82,54%).

Shin et al. (2005) conducted bankruptcy prediction research using SVM and NN methods. In the analysis, it was seen that SVM performed better than NN. In the analyzes, it was observed that SVM had higher accuracy and better classification performance than NN as a result of the reduction of the training set. In SVM, the selection of the core function and the determination of the optimal values of the parameters were seen to have a significant effect on the performance of the model. According to the test data set, 7-fold cross validation was performed and the mean classification accuracy value was found to be SVM (71,72%)> NN (61,04%).

Chandra et al. (2009) used NN, SVM, CART techniques to predict the failure of DOT-COM companies. The data set obtained from Wharton Research Data Services (WRDS) consisted of

120 unsuccessful and 120 successful DOT-COM companies. Based on the financial statements of 240 companies included in the sample, 24 financial ratios were selected. Out of these 24 variables calculated for financially successful and unsuccessful companies, 1-15 of them were determined as most used variables for bankruptcy prediction of finance companies and 16-24 of them were determined as sale, cash, income, market value and stock price variables. A 10-fold cross-validation technique was used for validation of the data set for all methods. The results were supported by the ROC (Receiver Operating Characteristic) curve. According to the results of the analysis, the performance of the methods for classification accuracy were CART> SVM> NN, respectively.

Akkaya et al. (2009) developed an artificial neural network model to predict the one year before financial failures of 52 businesses operating in ISE (renamed Borsa Istanbul in 2013) textile, chemistry, petroleum and plastics sectors during the 1998-2007 period. 28 successful and 24 unsuccessful businesses were determined according to the financial failure criteria, which were being bankrupt, being delisted from the stock market, having ceased operations, having incurred losses for 3 consecutive years or more. The data set was divided into three as training, validation and test data. Of the 21 businesses in the test set, 11 were in the successful group and 10 were in the unsuccessful group. As a result of the analysis, 9 of 11 successful businesses were classified correctly, 8 of 10 unsuccessful businesses were classified correctly, and the total classification accuracy rate was found to be 81.00%.

Li et al. (2010) examined whether there was a significant difference in terms of prediction and classification, when CART, KNN, SVM methods were compared with the classical statistical methods such as Multiply Discriminant Analysis (MDA) and Logistic Regression Analysis (Logit). Stepwise discriminant analysis was used as a variable selection method in the analyses using 30 financial ratios and a total of 153 successful and unsuccessful companies registered to the Shenzhen Stock Exchange and the Shanghai Stock Exchange. In the analyses, the classification accuracy was determined CART> SVM> kNN> MDAFS-CART> MDA, respectively.

Gepp et al. (2010) compared the classification performances of MDA, NN, C5.0 and CART models in their financial failure prediction. The classification and prediction ability of the C5.0 algorithm was clearly found to be the best classification technique. The C5.0 algorithm produced more complex trees compared to CART. The CART model had the most consistent predictability on misclassification coasts. DT methods performed better than NN and LA in predicting with six financial ratios and continuous data. It was stated that all of the different DT techniques performed better than MDA in order to achieve the classification between successful and unsuccessful businesses.

Chen (2011) analyzed with a total of 37 variables consisting of financial and non-financial variables, by taking 100 company data of 50 financially unsuccessful and 50 financially successful companies registered in Taiwan Stock Exchange between 2000-2007. C5.0, CART and CHAID and LA methods were used in the study. As the time of financial distress approached, the decision tree prediction model gave more accurate results. C5.0 algorithm's prediction accuracy was 88.80% for 8 pre-periods, while it was 97.01% for 2 pre-periods. For LA, the prediction accuracy before the 2- and 8-period prior to financial distress was 85.07% and 91.70%, respectively. It was concluded that the accuracy rate of the C5.0 algorithm was better than CART and CHAID.

Yakut (2012) created financial failure prediction models by using the 2002-2010 data of 60 successful and 60 unsuccessful businesses trading in BIST. From data mining techniques, C5.0

algorithm, SVM and NN were compared with each other to determine the best prediction method. NN method gave better results in general compared to C5.0 and SVM methods. When classified in terms of classification accuracy, NN>C5.0>SVM was found. According to the three methods, prediction results of one year before the failure achieved higher prediction than the results of 2, 3 and 4 years before, respectively.

Tsai et al. (2014) conducted a comprehensive study to compare three commonly used classification techniques: multilayer perceptron (MLP) NN, Support Vector Machines (SVM) and Decision Trees (DT). Experimental results with three public data sets indicated that DT communities of 80-100 classifiers using the enhancement method showed the best performance. The Wilcoxon signed rank test also concluded that DT communities performed significantly differently than other classifier communities.

Le and Viviani (2018) attempted to predict the financial failure of 3000 US banks, including 1438 failures and 1562 successful studies. Two conventional statistical methods, such as Discriminant analysis and logistic theorem, and three machine learning methods, such as Artificial neural network, Support Vector Machines and k-nearest neighbors, were used as methods. For each bank, the data were collected over a period of 5 years. The 31 financial ratios have been used obtained from the Bank's financial reports. The data were mixed to prevent the algorithm from memorizing the data. The data set is divided into 30% test samples for 70% training and data testing to learn the data. They observed that machine learning, ANNs and k-NN methods perform more effectively than traditional methods. ANN and the nearest neighboring algorithm proved to be extremely successful in accurately detecting financial failure, but in other methods they stated that this failure was low. The empirical result suggests that the neural network and the nearest neighboring methods are the most accurate. It was also found that SVM did not perform better than traditional statistical methods.

Yürük and Ekşi (2019) used the data of 140 businesses in the manufacturing sector traded in Borsa Istanbul (BIST) between 2008 and 2016. In this study, bankruptcy, taking part in the BIST detention market, cessation of operations, having a loss for two consecutive years and losing 10% of the asset amount were considered as financial failure criteria. The prediction performance of the models obtained by these two methods using Artificial Neural Network (ANN) and Support Vector Machine (SVM) was compared. The performance of the model was tested by calculating the area under the curve with ROC analysis. In test data, ANN showed 79.66% and SVM 72.88% prediction accuracy in (t-1) year, ANN 76.27% and SVM 71.19% prediction accuracy in (t-2) year, ANN 74.58% and SVM %71.19 prediction accuracy in (t-3) year.

Çöllü et al. (2020) evaluated the three-year financial status of 20 businesses in the textile, clothing and leather sectors registered in Borsa Istanbul (BIST) with the Altman Z score and identified successful and unsuccessful businesses. They determined the degree of correct classification of businesses by data mining algorithms such as CHAID, Exh-CHAID, CART and QUEST in terms of financial failure and the factors affecting financial failure. As a result of the analysis, the method with the highest prediction accuracy was found to be CART with 95.00% general classification accuracy. In addition, it was seen that financial success was affected by return on equity, current ratio, ratio of fixed assets to equity, ratio of trade receivables to assets, inventory turnover and interest coverage ratio.

In classification analyses conducted with SVM, k-NN and CART methods by Liang et al. (2015), it was found that the variable selection did not always improve performance of the models, especially for CART and SVM. The reason was because CART was able to identify important variables using many variable selection methods during the tree creation process, whereas input varibles were considered important in SVM. In the analysis conducted with China and Taiwan data set, classification accuracy was found SVM> CART> KNN, respectively.

According to the literature review it has been observed that in the field of financial failure prediction, Akkaya et al. (2009) used ANN method, Yakut (2012) NN, C5.0, SVM methods, Yürük and Ekşi (2019) ANN and SVM methods, Çöllü et al. (2020) used CHAID, Exh-CHAID, CART and QUEST methods. While there are studies abroad in the field of financial failure using some of the methods of NN and SVM, CART, KNN (e.g. Huang et al. (2004), Chandra et al. (2009), Li et al. (2010), Tsai et al. (2014), any financial failure prediction studies carried out with all of the NN and SVM, CART, KNN methods has been found in our country. It is thought that a study on measuring the performance of machine learning methods in the field of financial failure prediction and comparing the models under their distinctive features will add value to the literature. The main motivation for carrying out this research is to eliminate the relevant gap.

3. METHOD AND DATA

3.1. Data Set and Limitations of the Study

The financial institutions, mercantile and service businesses, which are traded in BIST, were excluded from the sample because they had different characteristics and the sample consisted of Borsa İstanbul manufacturing industry companies in order to prevent the problems of the sector differences. As much data as possible is required for machine learning methods to produce reliable results in predicting financial failure. Within the same sector, the largest number of companies (175) in 2021 is in the manufacturing sector. For this reason, analyzes were conducted with 86 companies that were registered in the manufacturing industry. Accounting practices and rules may differ in each country. The definition of financial distress by scientists is not always the same. Assuming the bankruptcy as the sole criterion of financial failure means that other options of a company, such as seeking merger paths, have been neglected (Geng et al., 2015, p.236). In this study, the criterias which are based on the financial and non-financial statements are used in the determination of the successful-unsuccessful companies. Table 1 shows the indicators of financial failure.

Table 1. Financial Failure Indicators

Financial Failure Indicators Based on Financial Statements	Negative value of shareholders' equity
	Reduction of at least 2/3 of the equity
	Reduced total assets by 10% or more
	Making a loss for the last two years or more
Financial Failure Indicator with The Material Disclosure Based on non Financial Statements	Permanent closure of BIST transaction sequence

According to the financial failure indicators that were based on the financial statements and not based on the financial statements, unsuccessful companies were identified by years. 2012 was considered as the year of failure because 2012 had the highest failure during the research period, and 2012 was accepted as the year of success among the successful examples in order to eliminate the inconvenience of evaluating the data of different years. Since the data of 1 and 2 years before the failure was needed, it was necessary to reach the data of 2010, 2011 and 2012 on a regular basis. Therefore, the data of 43 unsuccessful companies and 43 successful companies randomly selected among successful companies of 2012 were obtained from the BIST website.

Unsuccessful businesses may continue to operate, but it is far more unusual for successful businesses to suddenly fail. As the prediction time increases, the model accuracy starts to decrease (Jardin and Séverin, 2011, p.710) Although the models used in the literatüre (e.g. Yakut (2012), Yürük and Ekşi (2019)) are significantly different depending on the modeling method, the variables used and the sampling used, there is a common feature that the classification accuracy decreases significantly when the prediction time exceeds one year. Model accuracy decreases by 15% on average between 1 and 3 years. Some decisions may require a 1-year forecasting period for decision-makers, while long-term business decisions or investment decisions may require a longer period of time (Gepp and Kumar, 2015, p.398).

As can be seen in Table 2, 2012 was the year with the greatest failure in terms of companies. As the number of samples increased in statistical methods and machine learning methods, the reliability of the study increased. Therefore, 2012 has been considered as a year of failure for failed businesses and the year of success for successful businesses. If 1, 2 and 3 years before the failure had been predicted in our study, the data of 2009 would be needed. The effects of the global financial crisis have been felt in Turkey especially in 2009. Therefore, the financial data of 2009 reflect the effects of the crisis. Therefore, in order to take necessary precautions, models made 1 and 2 years ago with high accuracy rate were considered sufficient and used in our study. Table 2 shows the distribution of unsuccessful companies by years.

Table 2. Distribution of Failed Companies by Years

Years	Number of Failed Companies
2010	42
2011	44
2012	57
2013	55
2014	53
2015	50

Financial ratios are commonly used to reveal the financial state of businesses. Obtaining the ratios that are not dependent on the size of the businesses makes it possible to compare different size businesses (Divsalar et al., 2011, p.213). In financial failure prediction studies, financial ratios are generally selected according to three criteria. These criteria are widely use of ratios in the failure prediction literature, the availability of the information necessary to calculate these ratios, and decisions of the researchers based on their own experience (Alfaro et al. 2008, p.114).

Keasey and Watson (1987) compared the results obtained with three different models to determine which model predicted better among these three models, one of which was only based on financial ratios, one of which included non-financial variables, one of which used both the financial ratios and non-financial variables. As a result of the analysis, the model that used both financial ratios and non-financial variables were found to have better prediction results than the other two models (Keasey and Watson, 1987, pp.350-351). In this study financial ratios that are formed by the data obtained from the balance sheet and income statement of the businesses have been used. On the other hand financial statement footnote variables that are not based on the financial statement data and the variables that are not based on the financial statements obtained from the general information published in PDP-KAP (Public Disclosure Platform) have been used. ANN, SVM, CART and KNN used in the study are non-parametric methods. In non-parametric methods, there are no assumptions that the explanatory variables in each group fit a multivariate normal distribution, the variance covariance matrices of the groups are equal, and the correlation between the explanatory variables is as low as possible. Therefore, there is no need to convert variables (Jardin, 2016, p.240). In this study, it was investigated whether the reduction in the number of variables caused any decrease in the prediction accuracy of the models. If a high prediction accuracy is achieved with fewer variables, the relevant model results are shared in the study. Although the use of parametric methods in the study makes correlation analysis unnecessary, correlation analysis was performed to reduce the number of variables. Therefore, the values of the three variables, which had correlation with the other variables, were excluded from the data set and finally 14 variables were used in analyses. When determining the financial ratios that constitute the independent variables of the study, the ratios in the finance literature were taken into consideration. Appendix 4 provides information on the researchers using the financial ratios used in our study in their studies. The variables used in the study are shown in Table 3.

Table 3. Variables used in the Study

No	Quantitative Variables	No	Qualitative Variables
X1	Ratio of Inventories to Total Assets	**X9**	Whether or not it has been audited by four major auditing companies, Pricewaterhousecoopers-Deloitte Touche Tohmatsu- Kpmg- Ernst And Young
X2	Liabilities to Assets Ratio	**X10**	Number of independent board members
X3	Receivables Turnover Ratio	**X11**	Free float rate
X4	Fixed Asset Turnover Ratio	**X12**	Real and legal persons having 5% or more share or voting right in the capital- foreign capital share in non-public shares
X5	Operating Profit Margin	**X13**	Short term foreign currency debt USD maturity (1000)
X6	Return On Assets (ROA)	**X14**	Whether BIST is in the corporate governance index
X7	Assets Profitability Rate		
X8	Equity Profitability (ROE)		

Source: The literature was prepared by the authors as a result of the review.

3.2. Research Methodology

There are many programs, both commercial and open source, to implement Data Mining applications. RapidMiner (YALE), WEKA and R programs are among the most used ones (Dener et al., 2009, pp.1-2). Therefore, RAPIDMINER 9.2 program was used for ANN, CART, SVM and KNN analyzes in this study.

The conceptual structure of the study is shown in figure 1.

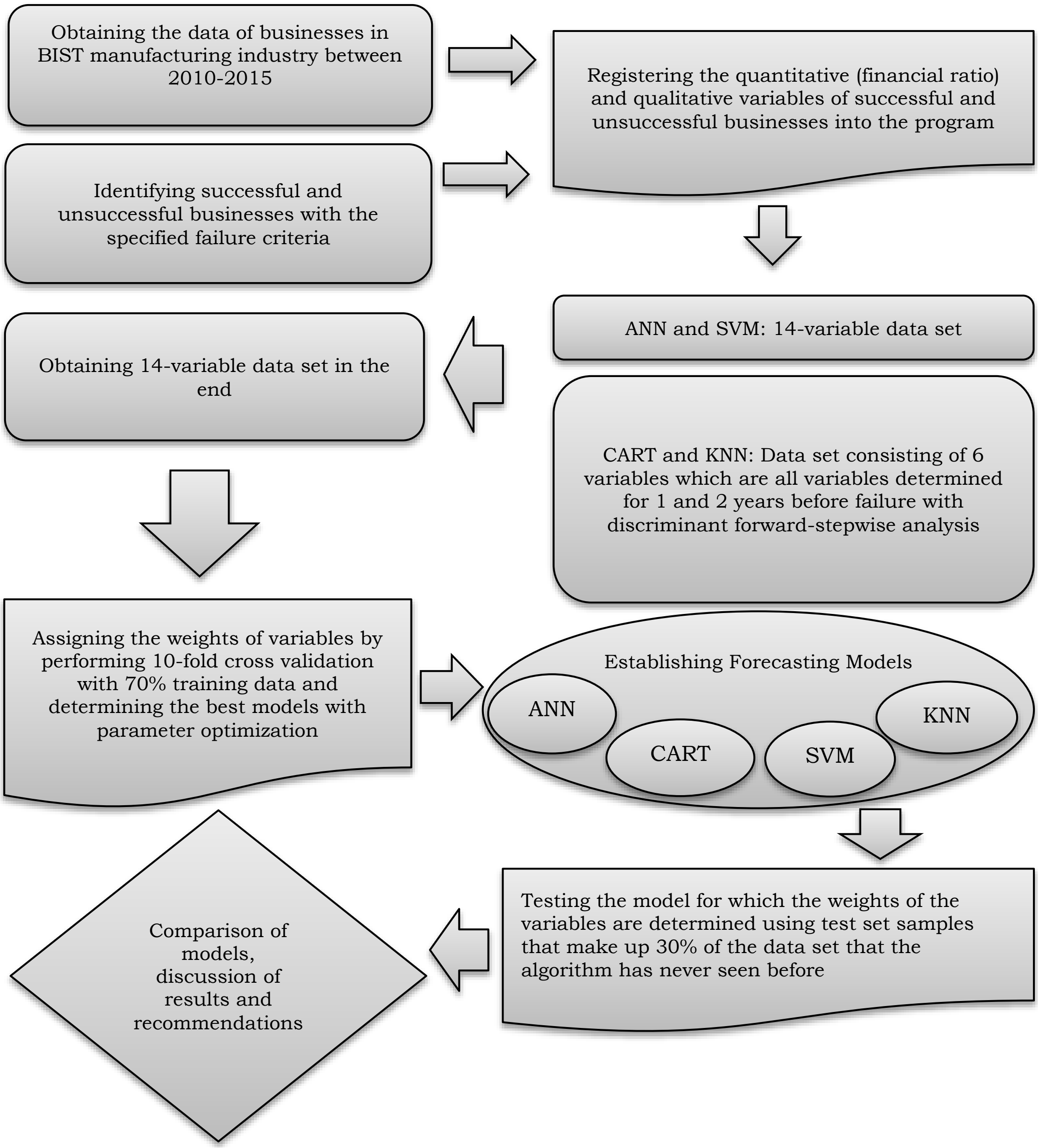

Figure 1. Conceptual Structure of the Study

3.3. Method

Machine learning is a sub-branch of artificial intelligence consisting of modeling and algorithms that make predictions with inferences from data using mathematical and statistical methods. The purpose of machine learning is to make accurate predictions. In doing so, it can be difficult to interpret prediction functions and relate them to a particular probability model. Supervised learning is the process of creating a machine learning model based on the training data set. In supervised learning, the learning of the algorithm is completed by using the training data, which consists of a large part of the data, and the learning phase is supervised using the test data. Supervised machine learning generally focuses on prediction and estimation problems (Akay, 2018, p.46).

There are important differences between machine learning algorithms/methods and ndrmeconometric applications. While econometrics focus on predicting causal effects and identifying causal relationships, machine learning offers tools that can summarize different relationships in data without dealing with causal relationships, and focuses on data-based model selection to make appropriate predictions. Machine learning often includes algorithms such as size reduction, model selection, and data analysis. While all data of the research are used in econometrics analysis, the data set in machine learning is divided into two as training and test data. While econometric analysis is applied in most cases in which the number of observations is greater than the number of variables, machine learning enables the analysis when the number of observations is smaller or the same number than the number of explanatory variables. Especially the fact that machine learning does not concentrate on causal relationships causes econometricians to stay distant from machine learning algorithms (Akay, 2018, p.47).

In K-fold cross-validation, the data is randomly divided into equal parts in k number. A part of it is used for test analysis, the rest is used for the training analysis. After that another part is used for test, the rest is used for training. Data mining analysis is performed at each stage and overall performance is obtained after all of the parts are tested. According to expert opinions, the most suitable value for number k was found 10 in experimental studies (Çelik et al., 2017, p.243). Gaganis (2009) stated that 10-fold cross-validation as a model validation type was one of the best methods to increase the detection accuracy, and over 75% detection accuracy was a good outcome in the social sciences. Figure 2 shows the k-fold cross-validation.

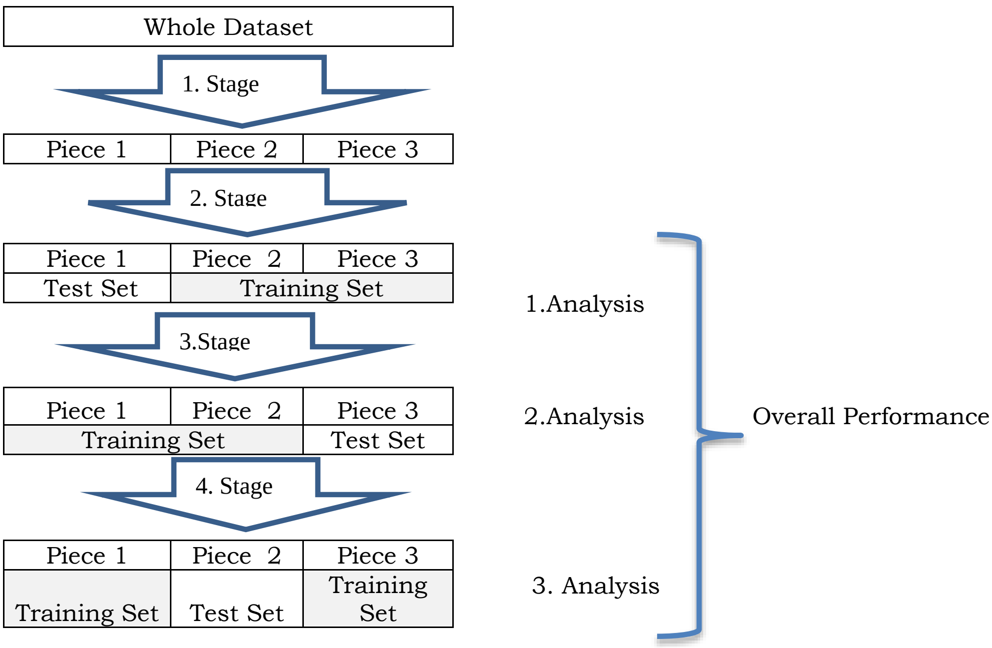

Figure 2. K-Fold Cross Verification
Source: Çelik et al.(2017)

They pointed out that in cases where different ratios are used to separate the training and test data set in the literature (e.g. Geng et al. (2015)) the standard deviation increases when the training ratio is 90% and the test ratio is 10%, and overtraining problem occurs in the case of

90:10. In order to better understand the effect of different baseline ratios between training and test set on generalization capacity, in the analyzes performed with 60:40, 75:25, 70:30 dataset separation, 70:30 combination was found to have the highest classification success. In determining the ratio of training and test sets, it is seen in the literature that 70% training and 30% test set are divided (e.g. Koç and Ulucan (2016)). In the study, data was divided into 70% training data and 30% test data. 10-fold cross validation was performed with the data constituting 70% of the data set, and validation was performed with 30% test data which the algorithm had never seen before. In the models using only 10-fold cross validation as a validation method, the samples used for the test can be the problem of learning and memorizing the data since there are samples that were previously seen by the algorithm in the training set during the creation of the model. Therefore, in our study, data were divided into 70% training and 30% test sample before using 10-fold cross-validation.
In the literature, where different rates are used in the separation of the training and test data set. For example, Geng et al. (2015) reported standard deviation to increase when given 90% of the training rate and 10% of the test rate. In order to avoid this problem, 70% of all the data were divided into two as training data and 30% as test data and 10-fold cross validation was performed to avoid this problem.

Table 4 shows all variabled determined for 2010 and 2011 with Discriminant Forward Stepwise Analysis.

Following the study of Geng et al. (2015), k-fold cross validaiton technique was used in this study to distribute the data in the best possible way, to increase the reliability of the results and to keep the possibility of memorizing the data at its lowest. In addition data set is divided into two parts as 70% training and 30% test data.

Table 4. All Variables Determined for 2010 and 2011 with Discriminant Forward Stepwise Analysis

No	**Variables**
X2	Liabilities to Assets Ratio
X6	Return on Assets (ROA)
X7	Assets Profitability Rate
X8	Equity Profitability (ROE)
X10	Number of Independent Board Members
X11	Free Float Rate

3.4. Methods used in the Research

Artificial Neural Network (NN), Classification and Regression Trees (CART), Support Vector Machine (SVM) and k-Nearest Neighbors (KNN) were used to compare classification performances of related methods.

3.4.1. Artificial Neural Network (ANN)

Artificial neural network model is composed of input layer, output layer and hidden layer, and there are neurons in each layer. The hidden layer can consist of more than one layer. The number of neurons in the output layer is equal to the output used. The input value of neurons uses the output values of previous layer neurons. Neurons in the hidden layer and the output layer process the signals coming to them by using an activation function and transmit them to this layer if there is a layer after it (Özçalıcı, 2017, p.72). Information in ANN is stored in the network weights. Learning in the artificial neural network takes place by changing these weights to fulfill a desired function. Learning in ANN occurs by changing the weights between nerves. Accordingly, dynamically changing networks can be trained in accordance with the learning rules of the weights on the interneural networks (Elmas, 2018, p.97). Multilayer feedforward neural networks are the most popular neural network algorithm used to train on. The weights are then changed to minimize the mean square error between the prediction of the network and the actual target. In general, the presence of too many neurons in the latent layer and too many networks form a neural network that lacks the ability to memorize and generalize data. One approach that can be used to prevent over-learning is n-fold cross validation (Enke and Thawornwong, 2005, p.930).

The number of neurons in the hidden layer (n), learning rate value (lr), momentum constant (mc) and number of repetitions (ep) are the ANN model parameters that need to be determined effectively (Kara et al., 2011, p.5314). The neuron consists of x_i, which is an input of several nodes multiplied by a weight in the previous stage (n) and then added to a threshold b. The transfer function is calculated by a mathematical function that determines a neuron output (Gaganis, 2009, p.213).

$$in = \sum_{t=1}^{n} w_i . x_i + b \tag{1}$$

The weights used in the advanced version ANN are renewed by correcting up to Δw each time.

$$W_1^{new} = w_1{}^{old} + \Delta w_1 \tag{2}$$

The most sensitive point of the algorithm is to find the Δw values and obtain the most suitable w weights. For this, a structure that minimizes the error that occurs each time is used. If the actual existing value is shown with g and the value obtained with w weights is shown as y, the error function E to be obtained by the method of least squares can be calculated as follows: (Silahtaroğlu, 2016, pp.124-125):

$$E_r = {}^1\!/_2\, e^2 = {}^1\!/_2\, (g - y)^2 \tag{3}$$

Each network is represented by an activation function, often a logistic function or a weighted sum of hyperbolic tangent inputs, indicating the strength of the relationship between two neurons and between each neuron. A stock price direction determination model designed using neural network calculates a Z score for a particular business, which can be expressed as follows, with a network consisting of a hidden layer, an output neuron, and an input layer representing the stock price direction (Öztemel, 2012, p.55).

$$Z = f\ (f(\textstyle\sum_{i=1}^{n} w_{ij} x_i + b_j)\ .\ (\sum_{j=1}^{p} w_j) + b \tag{4}$$

In the formula, f is the activation function, n is the number of variables, p is the number of hidden neurons, x_i is the input layer neurons, w_{ij} is the weights representing the relationships between the input layer and the hidden layer, w_j is the weights between the hidden layer and the output layer groups, b_j is the weights of the hidden neurons, and b is the weight of the output neuron (Jardin, 2016, p.241).

After weights are calculated on a set of data for learning, weights are tested to find out the level of learning by using the rest of the available data. When the effectiveness of the weights is verified after the test, the algorithm completes the learning process. Otherwise, w weights are corrected or recalculated (Silahtaroğlu, 2016, p.126). Geng et al. (2015) concluded that ANN performance was not affected by the variable selection, since the prediction accuracy of ANN models did not change significantly before and after the variable selection. In our study, when the number of variables was reduced, correct classification rates decreased significantly in the analyzes with 6 variables determined in forward stepwise discriminant analysis, thus the data set with all variables was used in the ANN analysis.

3.4.2. Classification and Regression Tree (CART)

The process of building a classification tree takes place in three steps which are the determination of the variable with the highest classification power that forms the root of the tree, the selection of the split point in the values of the corresponding variable and the splitting of the training data. After the decision tree is established, the process of pruning from the tip to the root is initiated to remove branches with lower foresight power (Alfaro et al., 2008, p.119). CART is a powerful, easy-to-use decision tree that explores key patterns and relationships in large, complex databases. CART is powerful because it can work with missing data and its trees contain easily understandable rules (Chandra, 2009, p.4832). When CART sets specific rules in the creation of the tree, it not only shows that a particular object belongs to a particular class, but also shows what variables are important in the classification of objects (Chuang, 2013, p.175).

CART does not consider lost data when calculating the branching criteria. The point with the highest value among the calculated Ψ(s/t) values is chosen as the node and the process is continued in the same way for all leaves (Silahtaroğlu, 2016, p.83).

$$\Psi(s/t = 2P_L P_R \sum_{j=1}^{M} \left| P(C_{j)} \right| t_L) - P(C_j|t_R)| \quad (5)$$

t: The node to branch

c: Criterion

L: Left side of the tree

R: Right side of the tree

P_L, P_R : Probability of an entry in the learning set to be on the right or left

$|P(C_j|t_L)$-$P(C_J|t_R)|$: Probability of an entry in the C-class to be on the right or left

Gini index is the measure of inequality between values in a frequency distribution. It is based on dividing the attribute values into two parts as left and right, calculating the Gini separately for each part and comparing the results obtained (Özkan, 2016, p.44). The Gini Index is calculated using equation 5, where g (t), pi are the probability of each category and c is the number of categories (Akpınar, 2014, p.212).

$$g(t) = 1 - \sum_{i=1}^{c} p_i^2 \quad (6)$$

3.4.3. Support Vector Machine (SVM)

Support Vector Machine (SVM) was suggested by Vladimir Vapnik, Berhard Boser and Isabelle Guyon in 1992. Compared to other classification methods, it is often preferred due to its high reliability, its resistance to rote learning and its nonlinear classification success despite the length of the training period. SVM is a supervised learning algorithm that aims to maximize the width between support points determined depending on the decision line (Akpınar, 2014, p.268). SVM is based on the optimal method that performs classification tasks by creating hyperplanes in a multidimensional space that separates states of different class labels. The SVM method provides an optimally separated hyperplane and the margin between the two groups is maximized. It has proven to be advantageous in fulfilling classification tasks with its excellent generalization performance (Li et al., 2017, p.790).

This method performs classification using a linear or nonlinear function. Several hyperplanes can be used to separate data sets from each other. It is best to choose those that have the largest gap between the two hyperplanes. This can be expressed as seen in equation 7:

$$\sum_{i=1}^{n} w_i \,.\, x_i + b = 0 \qquad (7)$$

Here w is the weight vector W= $\{w_1, w_2, \dots w_n\}$; n indicates the number of attributes. b indicates a constant number (Özkan, 2016, pp.170-171).

Support Vector Machine (SVM) has a learning ability that is not depend on the size of the variable area, as it can successfully classify even under conditions where the number of training examples is small. SVM uses a structural risk reduction rule to provide an optimized solution in training and prevents data from being memorized (Lin, 2014, p.2476). SVM, on the other hand, can obtain optimal solution with small training set size since it captures the geometric properties of the property space without determining the weights of the nets from the training data (Shin vd., 2005, p.127). The significant advantage of SVM is that it has high predictive performance when applying it to financial failure prediction. The purpose of the SVM is to find an optimum parting plane. These data samples that are closest to the parting hyper plane are called support vectors (Li and Sun, 2009, p.10086). When compared to other classification methods, SVM is the preferred method with its high reliability, resistance to memorizing, and success levels in non-linear classification, despite the long duration of training. SVM is a supervised learning algorithm that aims to maximize the width between the identified support points depending on the decision line (Akpınar, 2014, p.268). Kernel Model Weights are given in Appendix 3.

3.4.4. K-Nearest Neighbor Algorithm (KNN)

The object to be classified in the K-Nearest Neighbor (KNN) algorithm is assigned to the class of its closest neighbors or neighbors according to its attribute values. Since the number of neighbors playing an important role in the classification is indicated by k, the algorithm is called k-nearest neighbor algorithm. Determining the k-value in the algorithm is important in terms of efficiency (Akpınar, 2014, p.232). K-nearest neighbor algorithm (KNN) is one of the memory based methods and uses the distances between the observation values for the classification process. Euclidean distance formula is mostly used in the calculation of distances. By determining the k number in the closest neighbor algorithm, the number of the nearest neighbor is determined (Özkan, 2016, p.153). The k value in the algorithm is determined before the model is set up. Since the number of neighbors that are important in the classification is indicated by k, determining the k value is important for the efficiency of the algorithm. The high K value can cause points that are not like each other to come closer, on the other hand very small K value can cause some points that are like each other to be distributed to different classes (Silahtaroğlu, 2016, p.118). This method is based on calculating the distances of each of the observations in the sample set from a determined observation value and selecting the closest k observations. Euclidean distance formula is used for i and j points in calculating the distances (Özkan, 2016, p.141).

$$d(i,j) = \sqrt{\sum_{k=1}^{p} \left(X_{ik} - X_{jk}\right)^2} \qquad (8)$$

4. RESULTS

In this study CART, SVM and KNN and ANN methods analysis has been performed. The classification performance of the four methods used in the study was compared by specifying the distinctive features of the models. The determination of the parameters may affect the form of the model produced. Parameter optimization for classification algorithms that require parameter setting before model training is important for classification algorithms such as ANN and SVM is. In this study, study of Sun et al. (2014) was followed and parameter optimization was used in 4 machine learning methods.

4.1.Artificial Neural Network (ANN) Analysis and Results

Lower and upper values were assigned to the parameter values in order to obtain the model with the highest prediction and classification result in the study. The model that gives the highest prediction and classification result is determined by testing the lower and upper values assigned with the function of determining the best parameters and performance criteria with different parameter combinations. ANN parameters are shown in Table 5.

Table 5. ANN Parameters

Network Type	Multi-layer perseptron		
Learning Algorithm	Back propagation		
Learning Rule	Momentum		
Number of Nodes in Input Layer	14		
Number of Hidden Layers	1		
Number of Nodes in Hidden Layer	9		
Number of Nodes in Output Layer	2 (Successful or unsuccessful)		
Feature selection	14 Independent variable		
Verification Type	The data set was divided into 70% Training and 30% Test Set. 10-fold cross validation method was used on the sample which constituted 70% of the data set.		
Sample Selection Type	Stratified Sample Selection		
Activation Function	Sigmoid		
Learning Rate	Minimum: 0,00	Maximum: 0,30	Steps: 10
Momentum	Minimum: 0,00	Maximum: 0,20	Steps: 10
Training Cycle Number	Minimum: 1,00	Maximum: 500	Steps: 10

Table 6 shows the results of the model which gives the highest performance according to the different parameter values of ANN algorithm. The performance of the model depends on the algorithm structures and parameter values. Performances are measured by methods such as accuracy, precision, f measure and Kappa statistic (Özdağoğlu et al.,2017, p.70). It is necessary to briefly mention the kappa statistics in Table 6.

Kappa is a statistical method that measures the reliability of agreement between two or more observers. It is a nonparametric statistic because the variable in which compliance is evaluated is categorical (nominal). While “Cohen's kappa coefficient” examines the harmony between two observers, “Fleiss's kappa coefficient” is used when the number of observers is more than two.

Kappa value can get a value between (-)1 and (+)1 and the value found is interpreted as follows:

K = If +1, the results of the two observers are completely compatible with each other.

K = If 0, the harmony between two observers depends only on chance.

K = If -1, the two observers evaluate completely opposite to each other.

In the classification made by Fleiss, if the kappa value is 0.75 and above, it is considered to be perfect, between 0.40-0.75 as moderate-good, and below 0.40 as a poor fit (Kılıç, 2015, p.142).

Table 6. Model Performance Results of ANN Analysis (%)

Parameters	2 Years Ago (2010)	1 Year Ago (2011)
Accuracy	84,62%	92,31%
Classification error	15,38%	7,69%
Kappa	0,692	0,846
AUC	0,858	0,899
Precision	90,91%	100,00%
Recall	76,92%	84,62%
F measure	83,33%	91,67%
Learning rate	0,27	0,27
Momentum	0,02	0,10
Traning cycles	51	151

According to the table 6; 84,62% accurate prediction performance was found two years before the financial failure while all of the successful and unsuccessful businesses were classified correctly one year before the financial failure and prediction performance was 92,31% success. A three-layer ANN model image is given in figure 3.

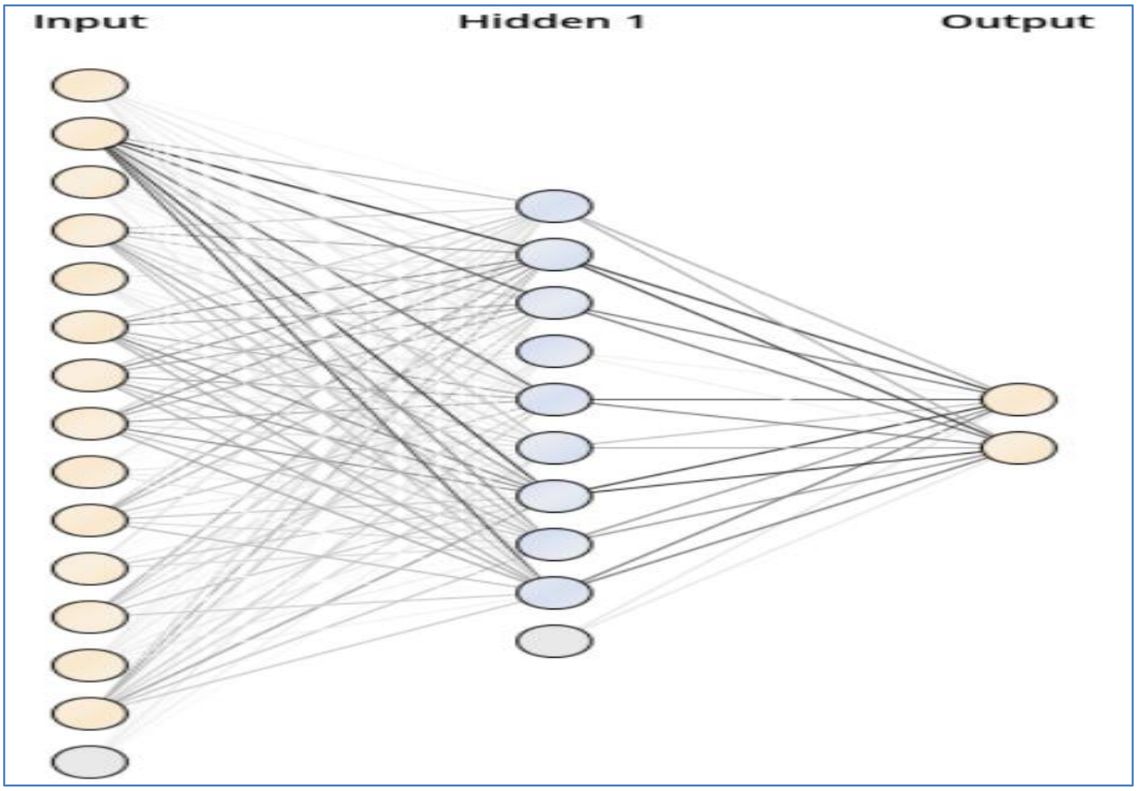

Figure 3. ANN Model Structure

4.2. Classification and Regression Tree (CART) Analysis and Results

In the financial failure prediction literature, the presence of unnecessary variables increases the noise level, complexity and uncertainty (Wu et al., 2006, p.330). Therefore, in CART analysis, the data set consisting of 6 variables were used with stepwise discriminant analysis. Table 7 presents the CART classification algorithm analysis parameters.

Table 7. CART Analysis Parameters

Parameters for Analysis	**Explanation**			
Data Set	Data set consisting of 6 variables, which are all of the variables determined for 1 and 2 years before failure with discriminant forward-stepwise analysis			
Verification Type	The data set was divided into 70% Training and %30 Test Set. 10-fold cross validation method was used on the sample which constituted 70% of the data set.			
Variable Number	6			
Sample Selection	Stratified sample selection			
Criterion of Split	Gini index			
Parameters for Analysis	**Minimum**	**Maximum**	**Steps**	**Scale**
Minimal Size For Split	1,0	4,0	10	Linear
Minimal Leaf Size	1,0	2,0	10	Linear
Minimal Gain	0,0	0,1	10	Linear
Maximal Depth	1,0	5	6	Linear
Confidence	0	0,25	-	-
Pre-pruning Number	0	3	-	-

Table 8 shows the model prediction performance results which give the highest classification results with CART analysis parameter optimization.

Table 8. CART Analysis Model Performance Results

Parameters	**2 Years Ago (2010)**	**1 Year Ago (2011)**
Accuracy	88,46%	96,15%
Classification error	11,54%	3,85%
Kappa	0,769	0,923
AUC	0,896	0,959
Precision	91,67%	100,00%
Recall	84,62%	92,31%
F measure	88,00%	96,00%
Minimal Size For Split	2	4
Minimal Leaf Size	2	1
Minimal Gain	0,0	0,0
Highest Depth	4	4

In Figure 4, X8- Equity profitability (ROE) was found to be the most important variable of the decision tree and formed the root. Of the businesses with equity profitability (ROE) less than or equal to 0,026, 3 of them were found to be successful and 21 were unsuccessful. X8- Equity profitability (ROE) variable was found as the branch of the tree in deciding the tree for businesses with Equity profitability (ROE) greater than 0,026. Four businesses with an Equity profitability (ROE) greater than 0,059 were found to be unsuccessful. Six businesses with an equity profitability (ROE) of less than 0,059 were found successful and one was unsuccessful.

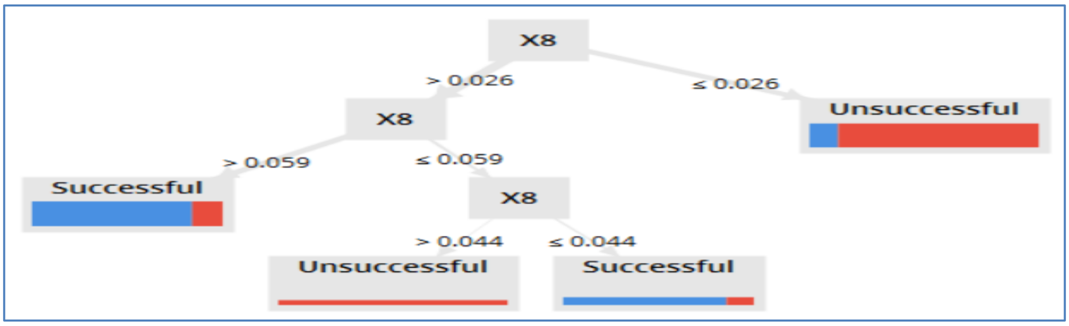

Figure 4. CART Decision Tree (2010)

In Figure 5, X8- Equity profitability (ROE) was found to be the most important variable of the decision tree and formed the root. For businesses with Equity profitability (ROE) greater than 0,067, two businesses with X8-Equity profitability (ROE) greater than 0,306, which is the branch determined by the tree, were found unsuccessful. 26 businesses with X8- Equity profitability (ROE) less than or equal to 0,306 were successful and three businesses were unsuccessful. X8-Equity profitability (ROE) was found as a branch in determining the businesses with Equity profitability (ROE) less than or equal to 0,067. 18 businesses with an equity profitability (ROE) less than 0,07 were found to be unsuccessful. The X6-Economic Profitability Rate (ROA) was found as a branch in the decision-making of the tree for businesses with Equity profitability (ROE) greater than 0,07. One business with Economic Profitability Rate (ROA) greater than 0,069 was successful, 6 businesses were unsuccessful. Three businesses with an Economic Profitability Rate (ROA) of less than 0,069 were successful and one business was unsuccessful.

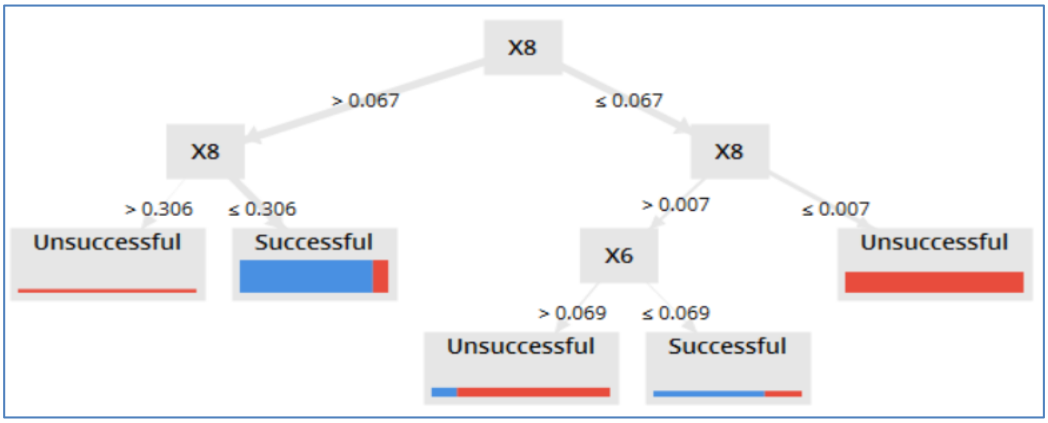

Figure 5. CART Decision Tree (2011)

4.3. Support Vector Machine Analysis and Results

SVM model weights are shown in Annex 3. Table 9 shows SVM Analysis Parameters.

Table 9. SVM Analysis Parameters

Parameters for Analysis	Explanation
Data Set	14 variable data set
Verification Type	The data set was divided into 70% Training and %30 Test Set. 10-fold cross validation method was used on the sample which constituted 70% of the data set.
Sample Selection	Stratified sample selection
Range Transformation	Minimum: 0,0 Maximum: 1,0
SVM.C	0,0312-0,125-0,5-2-8-32-128-512-2048-8192-32678-131072
SVM.kernel gamma	0,00003052-0,00012207-0,000488-0,00195-0,0078125-0,03125-0,125-0,5-2-8
Cache Size	200
Kernel Type	dot

Table 10 shows performance results of SVM analysis.

Table 10. SVM Analysis Model Performance Results

Parameters	2 Years Ago (2010)	1 Year Ago (2011)
Accuracy	92,31%	80,77%
Classification error	7,69%	19,23%
Kappa	0,846	0,615
AUC	0,959	0,858
Precision	86,67%	78,57%
Recall	100,00%	84,62%
F measure	92,86%	81,48
SVM.C	512	128
SVM,Kernel gamma	0,00003052	0,00195

4.4. KNN Analysis and Results

Table 11 shows KNN analysis parameters.

Table 11. KNN Analysis Parameters

Data Set	Data set consisting of 6 variables, which are all of the variables determined for 1 and 2 years before failure with discriminant forward-stepwise analysis
Verification Type	The data set was divided into 70% Training and %30 Test Set. 10-fold cross validation method was used on the sample which constituted 70% of the data set.
Sample Selection	Stratified sample selection
Range Transformation	Minimum: 0,0 - Maximum: 1,0
k number	Minimum: 1 - Maximum: 15
Measure types	Mixed Measures
Mixed Measure	Mixed Euclidean Distance

Table 12 shows the parameters that give the best result by the KNN algorithm.

Table 12. The Parameters that Give the Best Result by the KNN Algorithm

Parameters	2 Years Ago (2010)	1 Year Ago (2011)
Accuracy	80,77%	84,62%
Classification error	19,23%	15,38%
Kappa	0,615	0,692
AUC	0,500	0,917
Precision	83,33%	84,62%
Recall	76,92%	84,62%
F measure	80,00%	84,62%
KNN.k	1	5

4.5. Comparison and Evaluation of the Results

Table 13 shows the performance outcomes that predict the next 1 to 2 years performance results of the classification. In the 26 samples, which consist of 30% test data of the 84 samples, an equal number of random samples were selected from both financially successful and unsuccessful groups, and 13 businesses were included in each group. ANN analysis correctly predicted 22 of 26 test samples two years before financial failure (year 2010) and the overall prediction accuracy was found to be 84,62%. ANN analysis correctly predicted 24 of 26 test samples one year ago (2011) and the overall prediction accuracy was found to be 92,31%. CART analysis correctly predicted 23 of 26 test samples two years before financial failure (year 2010) and the overall prediction accuracy was found to be 88,46%. CART analysis correctly predicted 25 of 26 test samples a year ago (2011) and the overall prediction accuracy was found to be 96,15%. SVM analysis correctly predicted 24 of 26 test samples two years before financial failure (year 2010) and the overall prediction accuracy was found to be 92,31%. SVM analysis correctly predicted 21 of 26 test samples a year ago (in 2011) and the overall prediction accuracy was found to be 80,77%. KNN analysis correctly predicted 21 of 26 test samples two years before financial failure (year 2010) and the overall prediction accuracy was found to be 80,77%. KNN analysis correctly predicted 22 of 26 test samples one year ago (2011) and the overall prediction accuracy was found to be 84,62%.

Table 13. Performance Results of the Classification Methods used in the Study 1 and 2 Years Ago

Methods	For 2 Years Prior To Financial Failure (Year 2010) Classification Performance			Classification Performance For 1 Year Prior To Financial Failure (2011)		
	Failed	**Successful**	**Total**	**Failed**	**Successful**	**Total**
	76,92%	92,31%	84,62%	84,62%	100,00%	92,31%
ANN	10	12	22	11	13	24
	84,62%	92,31%	88,46%	92,31%	100,00%	96,15%
CART	11	12	23	12	13	25
	100,00%	84,62%	92,31%	84,62%	76,92%	80,77%
SVM	13	11	24	11	10	21
	76,92%	84,62%	80,77%	84,62%	84,62%	84,62%
KNN	10	11	21	11	11	22

In this study, we used Chandra et al. (2009)'s study as an example and we found that the results are supported by the ROC curve. Comprehensive evaluation of classification performance was carried out by the ROC. The ROC curve plots the percentage of the model's "hits" (ie true positives) on the vertical axis and the 1-specificity or percentage rates of "false alarms" on the horizontal axis. The result is a sloping curve rising from the 45° line to the upper left corner. The closer the bending sharpness is to the upper left corner, the higher the accuracy of the model. The area under the curve (AUC) can be considered as the average of misclassification rates according to all possible selections of various cut-off points (Gaganis, 2009, p.222). The ROC curve of two years ago is shown in Figure 6 and one year ago in Figure 7.

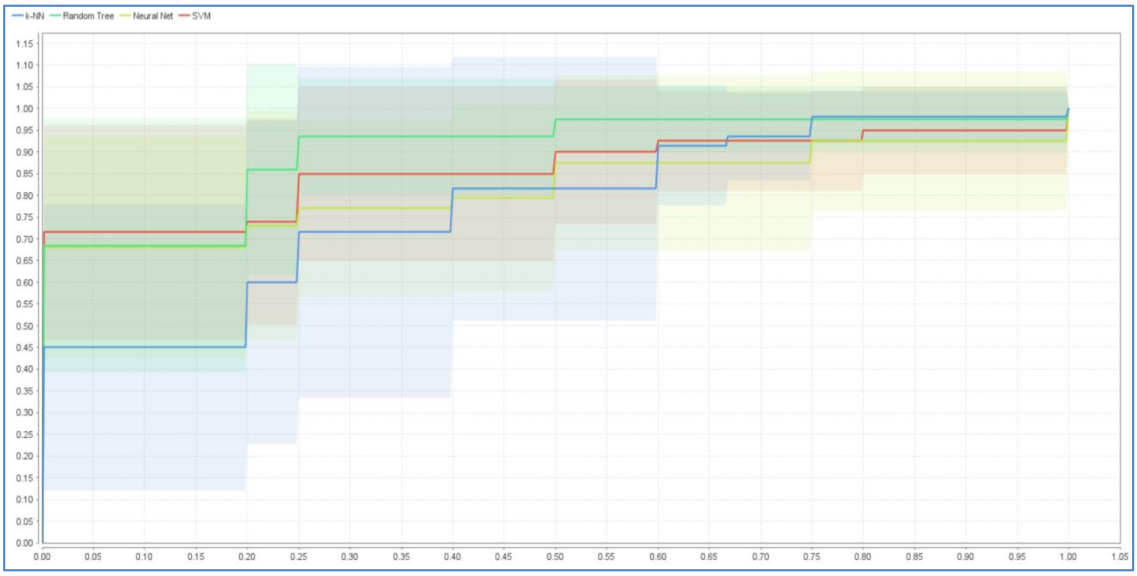

Figure 6. ROC Curve (2010)

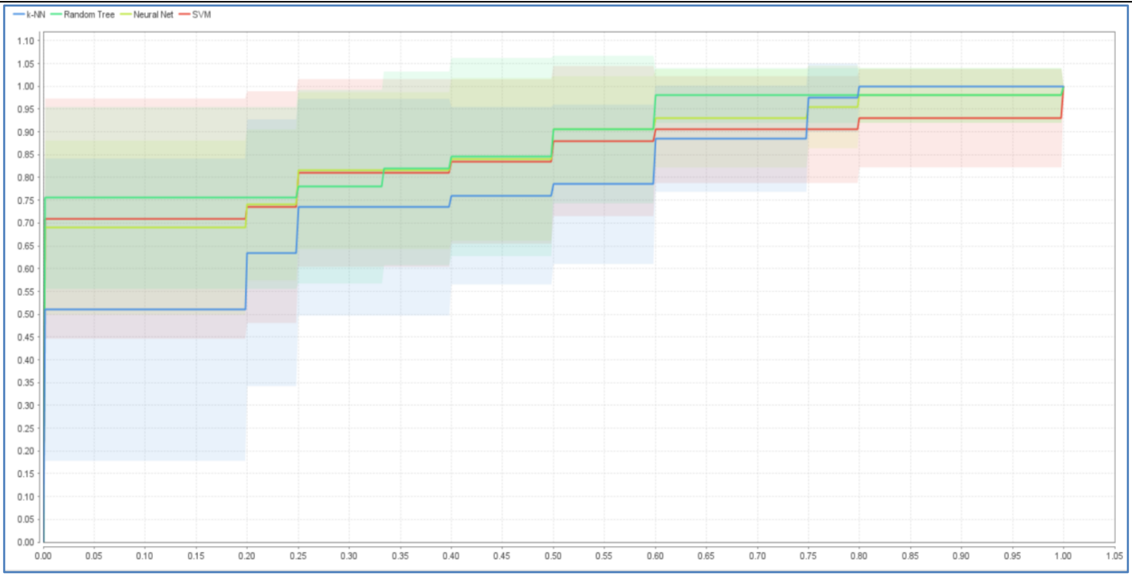

Figure 7. ROC Curve (2011)

Gepp et al. (2010) concluded that the DT model was better than the ANN and SVM models in terms of classification performance. CART decision tree model in this study showed higher prediction performance from ANN model one and two years before the financial failure and one year before the SVM model. SVM model showed higher classification performance from CART two years before the financial failure. In study of Li et al. (2010), the classification accuracy of the methods used were found CART>SVM>kNN>MDAFS-CART>MDA, respectively (Li et al., 2010, p.5901). This result is consistent with the results of the analysis performed with 2011 data one years before the failure in our study. CART model came after SVM in terms of prediction two years ago. CART model was found to have higher prediction performance than KNN in two years. The prediction performance of SVM decreased as we approached the year of failure and the classification performance was found to be CART> ANN> SVM> KNN. Li et al. (2010) found that the analysis carried out with all variables had higher classification accuracy when compared to the CART analysis using the variables selected by step MDA (Li et al., 2010, p.5903). This result is not consistent with our study. In this study, CART analysis conducted with six variables determined as a result of stepwise discriminant analysis was found to be the method with the highest prediction performance one year ago.

Geng et al. (2015), it was observed that the classification performance of ANN was higher than the DT and SVM classification accuracy. This result is not compatible with our study findings. The ANN model showed higher prediction performance from the SVM one year ago, but failed to obtain higher prediction performance from the CART decision tree model one and two years before the failure.

Liang et al. (2015) found that the selection of variables did not always improve the prediction performance in classification techniques carried out with variables obtained as a result of the selection of variables (Liang et al. 2015, p.289). This result is also valid in our study. ANN and SVM analyses were carried out with 14 independent variables consisting of all variables because ANN and SVM analyses results showed low classification performance due to variable selection. On the other hand, CART and KNN analyses showed sensitivity to the selection of variables and it was observed that the model created by using 6 variables determined by stepwise discriminant analysis yielded better classification performance than the model using all variables. Table 13 shows the performance results of the classification methods used in the study before one and two years. In the 26 samples, which consist of 30% test data of the 84 samples used in the study, an equal number of random samples were selected from both the financially successful and unsuccessful groups, and 13 businesses were included in each group.

5. CONCLUSION

In this study, following the study of Jardin (2010), the relationship between the ability and structure of the models was examined to predict financial failure accurately by using parameter optimization obtained with different parameter values and variable selection. In this study, financial failure prediction was made 1 and 2 years ago by using 2010-2012 data of 86 firms registered in manufacturing industry that were registered in Borsa Istanbul (ISE; renamed Bourse Istanbul in January 2013). Artificial Neural Networks, Classification and Regression Trees, Support Vector Machines and K-Nearest Neighbors Algorithm were used in this study to compare classification performances of related methods. As a result of the analysis, the overall classification accuracy from the highest to the lowest was SVM (92,31%), CART (88,46%), ANN (84,62%) and KNN (80,77%) 2 years before the financial failure. The overall classification accuracy from the highest to the lowest was CART (96,15%), ANN (92,31%), SVM (80,77%) and KNN (84,62%) 1 year before the financial failure. Gaganis (2009) stated in his study that 10-fold cross-validation as a type of model verification was one of the best methods to increase detection accuracy, and detection accuracy over 75% was a good result in the field of social sciences. According to Gaganis (2009) classification, SVM (92.31%) can be considered very good, CART (88.46%), ANN (84.62%) and KNN (80.77%) good for two years ago, CART (96.15%), ANN (92.31%) can be considered very good, and SVM (80.77%) and KNN (84.62%) good for one year ago. Another important result obtained as a result of the analyzes is that Return on Equity (ROE) and Return on Assets (ROA) were found as important variables in the creation of the CART decision tree.

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In the following phrases, we present the aspects of our study that differ from the literature and also we present the contributions of our study; i) financial ratios and non-financial failure criteria obtained from the non-financial BIST Public Disclosure Platform were used as the criteria for financial failure. ii) in addition to the financial statement data, non-financial variables obtained from BIST Company news and announcements were used as independent variables. iii) as a result of the use of variable selection methods such as correlation analysis and forward stepwise discriminant analysis, CART and KNN analyses were carried out with variables determined by stepwise discriminant analysis. iv) In order to eliminate the problem of memorizing the data, the data set was divided into 70% training and 30% test, and a 10-fold cross validation method was used to obtain a more reliable analysis result. v) parameter optimization was used in which parameter values were obtained by entering different parameter values into the program. vi) important variables were determined in the classification as a result of CART analysis.

Because of the difference of accounting standards between countries, the results of this study may limit the generalizability of implementation in businesses of other countries. However, whether or not it will help to improve the prediction performance of studies to be carried out in other countries will be clarified by the researches. Success-failure terms sometimes may not be sufficient in terms of time-based analyses of businesses and taking the necessary measures in some cases, so fuzzy logic methods can be used in the analyses including the rankings of businesses. It would be also interesting to apply the methods used in this study to large amounts of data from service industries and trading companies and to see how different the prediction values in the rates are. In future studies, filter and wrapper feature selection methods can be used in the variable selection stage as they are the commonly used methods in bankruptcy prediction and credit scoring. In addition to using single classification techniques to develop prediction models, combining multiple classifiers with bagging and boosting combination methods and examining the performance of community classifiers can be considered. It is thought that it will be beneficial to use other machine learning methods or use them together with traditional methods in order to improve the prediction performance of the models.

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APPENDIX

Appendix 1. Artificial Neural Network Weights 2 years ago (Year 2010)

INPUT LAYER	HDDEN LAYER									
Independent variable	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	Node 8	Node 9	Threshold
	Sigmoid									
X1	-0,061	0,176	0,208	0,129	0,132	-0,022	-0,124	-0,091	0,202	
X2	-0,706	1,991	1,510	0,224	1,406	-0,504	-1,761	-0,965	1,484	
X3	0,071	0,167	0,124	0,150	0,157	0,039	-0,039	0,028	0,178	
X4	0,466	-0,771	-0,527	0,137	-0,487	0,363	0,884	0,578	-0,513	
X5	0,111	-0,193	-0,081	0,020	-0,146	0,118	0,257	0,164	-0,127	
X6	0,519	-1,037	-0,800	0,007	-0,749	0,457	1,108	0,685	-0,750	
X7	0,406	-1,048	-0,766	-0,195	-0,735	0,269	0,971	0,498	-0,738	
X8	0,409	-1,027	-0,756	-0,167	-0,753	0,301	1,032	0,555	-0,789	
X9	0,231	0,064	0,049	0,034	-0,022	0,195	0,147	0,222	-0,002	
X10	0,266	-0,802	-0,632	-0,070	-0,537	0,185	0,506	0,340	-0,583	
X11	-0,264	0,003	0,041	-0,037	-0,003	-0,184	-0,476	-0,324	0,031	
X12	0,016	0,682	0,484	0,198	0,448	0,053	-0,497	-0,056	0,457	
X13	0,153	-0,136	-0,077	0,178	-0,059	0,156	0,193	0,150	-0,112	
X14	0,387	-0,726	-0,512	0,069	-0,471	0,380	0,881	0,506	-0,487	
Bias	-0,108	-0,024	-0,043	-0,182	-0,051	-0,136	-0,050	-0,007	-0,014	
Output layer (Successful) Sigmoid	0,725	-1,797	-1,257	-0,110	-1,218	0,564	1,793	0,966	-1,233	0,237
Output layer (Failed)	-0,767	1,739	1,312	0,121	1,172	-0,580	-1,747	-0,994	1,279	-0,228

Appendix 2. Artificial Neural Network Weights 1 year ago (Year 2011)

Input Layer	Hidden Layer									
Independent variable	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	Node 8	Node 9	Threshold
	Sigmoid									
X1	-0,827	2,166	1,369	0,319	-0,222	0,198	-0,633	-0,389	-0,307	
X2	-0,841	1,522	1,197	0,411	-0,317	0,727	-0,718	-0,458	-0,431	
X3	0,731	-0,360	-0,249	0,066	0,460	-1,337	0,701	0,499	0,475	
X4	1,404	-1,567	-1,038	-0,100	0,563	-2,199	1,159	0,798	0,743	
X5	-0,314	0,248	0,110	-0,131	-0,094	0,175	-0,169	-0,105	-0,133	
X6	-0,704	0,889	0,702	0,163	-0,428	-0,515	-0,708	-0,594	-0,487	
X7	2,533	-3,816	-2,536	-0,559	1,093	-6,229	2,132	1,354	1,342	
X8	1,471	-2,532	-1,718	-0,473	0,593	-4,206	1,256	0,685	0,722	
X9	0,424	1,476	1,124	0,098	-0,097	-0,731	0,198	0,148	-0,004	
X10	0,139	-1,359	-0,867	-0,173	0,099	-0,084	0,096	0,165	0,131	
X11	-1,623	0,704	0,547	0,083	-0,441	0,362	-1,192	-0,784	-0,626	
X12	0,123	-0,091	-0,016	0,176	-0,052	0,444	-0,019	-0,047	-0,093	
X13	0,752	-0,702	-0,441	0,143	0,318	-1,194	0,622	0,499	0,398	
X14	0,635	-0,663	-0,268	0,215	0,527	-0,650	0,613	0,627	0,575	
Bias	-0,192	0,038	-0,078	-0,267	-0,152	0,236	0,166	-0,146	-0,160	
Output layer (Successful) Sigmoid	1,902	-2,882	-1,910	-0,320	0,871	-3,854	1,584	1,081	1,060	0,700
Output layer (Failed) Sigmoid	-1,898	2,894	1,887	0,310	-0,880	3,886	-1,558	-1,106	-1,008	0,725

Appendix 3. Kernel Model Weights

WEIGHTS	YEAR 2010	YEAR 2011
w(X1)	0,441	13,646
w(X2)	0,572	70,923
w(X3)	-0,304	-18,672
w(X4)	-0,769	-21,592
w(X5)	0,452	-122,968
w(X6)	0,070	55,858
w(X7)	-6,860	-74,797
w(X8)	0,871	-108,770
w(X9)	0,385	15,713
w(X10)	0,149	-11,449
w(X11)	-0,236	25,778
w(X12)	-0,088	5,951
w(X13)	-9,069	5,532
w(X14)	-0,697	-15,342
Bias (offset)	-0,348	68,172

Appendix 4. Information on the researchers using the financial ratios used in our study in their studies.

Independent variables	Financial Ratios	Author Name and Publication Year
X1	Inventory to Total Assets Ratio	Akkaya et al. (2009), Chen (2011), Terzi (2011), Yakut (2012), Kaygın et al. (2016)
X2	Liabilities to Assets Ratio	Ko and Lin (2006), Li and Sun (2009), Akkaya et al. (2009), Divsalar et al. (2011), M.Y.Chen (2011), Kılıç (2011), Li and Sun (2011), Elmas et al. (2011), Galego et al. (2012), Yakut (2012), Lin and Liang (2014), Geng et al (2015), Kaygın et al. (2016)
X3	Receivables Turnover Ratio	Ko and Lin (2006), Li and Sun (2009), Çelik (2009), Akkaya vd. (2009), Li and Sun (2011), Elmas vd. (2011), Kılıç and Seyrek (2012), Yakut (2012), Chuang (2013), Lin and Liang (2014), Kaygın vd. (2016)
X4	Fixed Asset Turnover Ratio	M.Y.Chen (2011), Li and Sun (2011)
X5	Operating Margin Ratio	Li and Sun (2011), Divsalar et al (2011), M.Y.Chen (2011), Elmas et al. (2011), Chuang (2013), Lin and Liang (2014), Kaygın et al. (2016)
X6	Return On Assets (ROA)	Ko and Lin (2006), Li and Sun (2009), Divsalar et al. (2011), Li and Sun (2011), Galego et al. (2012), Yakut (2012), Chuang (2013), Lin and Liang (2014), Geng et al (2015)
X7	Return On Total Assets (ROTA)	Alfaro et al (2008), Li and Sun (2009), M.Y.Chen (2011), Li and Sun (2011), Divsalar et al (2011), Galego et al (2012), Lin and Liang (2014), Kaygın vd. (2016)
X8	Return On Equity (ROE)	Ko and Lin (2006), Li and Sun (2009), Çelik (2009), Akkaya et al. (2009). Chen (2011), Li and Sun (2011), Galego et al. (2012), Yakut (2012), Chuang (2013), Lin and Liang (2014), Kaygın et al. (2016)
X9	Being Audited by Four Major Audit Firms (Pricewaterhousecoopers- Deloitte Touche Tohmatsu- Kpmg- Ernst And Young)	Added by the authors.
X10	Number of independent board members	
X11	Free float rate	
X12	Real and legal persons having 5% or more share or voting right in the capital- foreign capital share in non-public shares	
X13	Short term foreign currency debt USD maturity (1000	
X14	Whether BIST is in the corporate governance index	

GENİŞLETİLMİŞ ÖZET

Amaç

Bu çalışmada Borsa İstanbul İmalat Sanayi Sektörüne kayıtlı 86 firmanın, 2010-2012 dönemine ait verileri kullanılarak 1 ve 2 yıl öncesinden finansal başarısızlık tahmini yapılmıştır. Araştırmanın birinci amacı belirlenen değişkenlerle uyumlu çalışan, tahmin doğruluğu yüksek modellerin geliştirilmesidir. Araştırmanın ikinci amacı ise çalışmada kullanılan ANN, CART, SVM, KNN yöntemlerine ait tahmin gücü yüksek modellerin belirlenmesi ve elde edilen modellerin ayırt edici özellikleri altında tahmin performansının karşılaştırılmasıdır.

Yöntem

Bu çalışmada, başarılı ve başarısız işletmelerin belirlenmesi için finansal tablolara dayalı olan dört finansal başarısızlık göstergesi ve finansal tablolara dayalı olmayan bir finansal başarısızlık göstergesi kullanılmıştır. Finansal başarısızlık kriterleri kullanılarak finansal başarısız örnekler beirlendikten sonra aynı sayıda tesadüfi olarak seçilen finansal başarılı olan örnekler belirlenmiştir. Analizlerde literatür incelemesi sonucunda belirlenen 8 mali tablolara dayalı nicel ve 6 mali tablolara dayalı olmayan nitel değişken kullanılmıştır. Araştırmada sınıflandırma ve tahmin amacıyla Yapay Sinir Ağları (ANN), Sınıflandırma ve Regresyon Ağaçları (CART), Destek Vektör Makineleri (SVM) ve K-En Yakın Komşular Algoritması (KNN) yöntemleri kullanılmıştır. Değişken sayısının azaltılmasının tahmin performansı üzerindeki etkisini incelemek amacıyla diskriminant ileri adımlı analiz kullanılmıştır. CART ve KNN analizleri tüm veri setini oluşturan 14 değişken ile kıyaslandığında 6 değişken ile daha yüksek tahmin ve sınıflandırma sonucu elde etmiştir. Bu nedenle CART ve KNN analizleri 6 değişkenli veri seti kullanılarak gerçekleştirilmiştir. ANN ve SVM analizlerinde diskriminant ileri adımlı analiz kullanılarak seçilen 6 değişkenle yürütülen analiz sonucuna kıyasla 14 değişkenli veri seti kullanılarak yürütülen analiz sonuçları daha yüksek bulunmuştur. Bu nedenle ANN ve SVM analizleri 14 değişkenli veri seti kullanılarak gerçekleştirilmiştir. Doğrulama yöntemi olarak tüm veri seti %70 eğitim seti, %30 test verisi olarak ikiye ayrılmış, ayrıca 10 katlı çapraz doğrulama yöntemi kullanılmıştır. Parametre optimizasyonu kullanılarak programa girilen alt ve üst değerler tek tek denenerek en yüksek tahmin ve sınıflandırma sonucunu veren modeller belirlenmiştir. Çalışmada kullanılan yöntemlerin sınıflandırma performansları ROC Eğrisi ile karşılaştırılmıştır.

Bulgular

Analiz sonucunda, finansal başarısızlıktan iki yıl önce en yüksekten düşüğe genel sınıflandırma doğruluğu SVM (%92,31), CART (%88,46), ANN (%84,62), KNN (%80,77) ve olarak bulunmuştur. Finansal başarısızlıktan bir yıl önce en yüksekten en düşüğe genel sınıflandırma doğruluğu CART (%96,15), ANN (%92,31), SVM (%80,77) ve KNN (%84,62) olarak elde edilmiştir. ANN, finansal başarısızlıktan iki yıl öncesinde (2010 yılı) 26 test örneğinin 22'sini doğru tahmin etmiş ve genel tahmin doğruluğu %84,62 olarak bulunmuştur. ANN, bir yıl öncesinde (2011 yılı) 26 test örneğinin 24'ünü doğru tahmin etmiş ve genel tahmin doğruluğu %92,31 olarak bulunmuştur. CART, finansal başarısızlıktan iki yıl öncesinde (2010 yılı) 26 test örneğinin 23'ünü doğru tahmin etmiş ve genel tahmin doğruluğu %88,46 olarak bulunmuştur. CART, bir yıl öncesinde (2011 yılı) 26 test örneğinin 25'ini doğru tahmin etmiş ve genel tahmin doğruluğu %96,15 olarak bulunmuştur. SVM, finansal başarısızlıktan iki yıl öncesinde (2010 yılı) 26 test örneğinin 24'ünü doğru tahmin etmiş ve genel tahmin doğruluğu %92,31 olarak bulunmuştur. SVM, bir yıl öncesinde (2011 yılı) 26 test örneğinin 21'ini doğru tahmin etmiş ve genel tahmin doğruluğu %80,77 olarak bulunmuştur. KNN, finansal başarısızlıktan iki yıl öncesinde (2010 yılı) 26 test örneğinin 21'ini doğru tahmin etmiş ve genel tahmin doğruluğu %80,77 olarak bulunmuştur. KNN, bir yıl öncesinde (2011 yılı) 26 test örneğinin 22'sini doğru tahmin etmiş ve genel tahmin doğruluğu %84,62 olarak bulunmuştur. CART karar ağacının oluşturulmasında önemli değişkenler olarak Özsermaye kârlılığı (ROE) ve Ekonomik Kârlılık Oranı (ROA) bulunmuştur.

Sonuç

Bu çalışmada Borsa İstanbul İmalat Sanayi Sektörüne kayıtlı 86 firmanın, 2010-2012 dönemine ait verileri kullanılarak 1 ve 2 yıl öncesinden finansal başarısızlık tahmini yapılmıştır. Araştırmada 8 mali tablolara dayalı nicel ve 6 mali tablolara dayalı olmayan değişken kullanılmıştır. Yapay Sinir Ağları (ANN), Sınıflandırma ve Regresyon Ağaçları (CART), Destek Vektör Makineleri (SVM) ve K-En Yakın Komşular Algoritması (KNN) yöntemlerinin tahmin performansı yöntemlerin ayırt edici özellikleri altında karşılaştırılmıştır. Analiz sonucunda, finansal başarısızlıktan iki yıl önce en yüksekten düşüğe genel sınıflandırma doğruluğu SVM (% 92,31), CART (%88,46), ANN (% 84,62), KNN (%80,77) ve olarak bulunmuştur. Finansal başarısızlıktan bir yıl önce en yüksekten en düşüğe genel sınıflandırma doğruluğu CART (% 96,15), ANN (%92,31), SVM (% 80,77) ve KNN (%84,62) olarak elde edilmiştir. CART karar ağacının oluşturulmasında önemli değişkenler olarak Özsermaye kârlılığı (ROE) ve Ekonomik Kârlılık Oranı (ROA) bulunmuştur. Çalışmada elde edilen dört modelin finansal başarı/başarısızlığı bir ve iki yıl öncesinden yüksek oranda tahmin etmesi, ilgililerin kullandıkları modeller içerisine bu çalışmada elde edilen modelleri dâhil edebileceklerini göstermektedir.