International Journal of Social Science Research and Review

http://ijssrr.com
editor@ijssrr.com
Volume 7, Issue 2
February, 2024
Pages: 111-125

Predicting Financial Failure in Companies by Employing Machine Learning Methods

Safak Sönmez SOYDAS[1]; Handan CAM[2]

[1] İrfan Can Kose Vocaional High School, Gümüşhane University, Gümüşhane, Turkey

[2] Department of Management Informatıon Systems, Gumushane University, Gumushane, Turkey

E-mail: safaksoydas@gumushane.edu.tr; hcam@gumushane.edu.tr

http://dx.doi.org/10.47814/ijssrr.v7i2.1827

Abstract

It is utterly crucial for the companies trading in a country to sustain their activities and the welfare they would deliver to the country's economy. The worldwide economic globalization and the outbreaks of economic crises adversely influence the economies of the states as well as trading companies. It has become imperative for companies to attain good financial management and to take the vital precautions prior to failure either to prevent the existing companies from being influenced by these crises or to be less affected by them within the framework of all these circumstances. The study aims to generate a prediction and classification model in which the dependent variable, which is generated by taking into account the profit and loss criteria of the companies that maintain their activities, as well as independent variables by considering the generally accepted financial data of 178 manufacturing companies trading in Borsa Istanbul between the years 2015-2019, are used by employing machine learning methods. It also aims to assess the effectiveness of machine learning techniques in predicting failure. By courtesy of the comparative analysis, Machine learning methods of companies operating in Borsa Istanbul yield financially acceptable results in predicting and classifying successful-unsuccessful companies.

Keywords: *BIST; Financial Failure; Financial Ratios; Machine Learning*

1. Introduction

Since there is no consensus on the extent to which a company clearly identify when it is in financial distress, it has become an issue that needs to be resolved in the related academic literature (Onyırı, 2014). Financial failure is decsribed as the failure of a company to fulfill its financial responsibilities. Operationally, a company is supposed to fail once the following situations occur: an over-indebted bank account, bankruptcy, or non-payment of stocks Beaver, (1966).

Pindado et al. (2008), classified a company as unsuccessful in financial terms not only once the company bankrupts, however, when it fulfills the generally-accepted as financial failure criteria:

(1) Its financial expenses exceed its earnings before interest and taxes, depreciation and amortization for 2 successive years, steering the company into a circumstance in which it may not create sufficient funds to meet its financial obligations;
(2) A plunge in the market value emerges for 2 successive terms.

Moreover, financially distressed firms would exhibit certain expected features: they have incurred losses recently, had high leverage, had low and volatile stock returns, and had low cash holdings Campbell et al.,(2010). In particular, financial distress may be comprised of sustained or large profit decline, deferred debt and interest payment, default or deferred dividend payment, or even bankruptcy Sun and Li (2012). Common symptoms and causes of failure consist of lack of financial information, inability to identify capital plans, insufficient protection in presence of unpredicted circumstances, poor debt management, and hardships in abiding by appropriate operating discipline Chen and Du (2009). It has been suggested that the profitability ratio of companies for the few years before the failure date is a crucial indicator of failure. Besides, low profitability combined with high debt increases the predicted probability of failure in comparison to circumstances in which both impacts occur at once. Similarly, studies have revealed that the factors of financial distress include inadequate capital and excessive debt Mselmi et al., (2017). Administrative problems, the emergence of unexpected problems in the sector in which the company operates, and finally other causes (natural disasters, etc.) are indicated as the reasons for financial distress in the literature. Financial failure has been utterly attributed to internal reasons in the literature, and it was stated that external reasons were less effective (Aksoy, 2018; Akgün, 2013). It is also useful to mention three reasons that trigger financial distress. These reasons are the downturn of the industry, high-interest expense, and poor firm performance relative to the industry Asquith et al., (1991). Companies that fail to detect their financial distress and take action at an early stage would encounter bankruptcy, which not only leads to great harm to shareholders, creditors, managers, and other interests but also influences the stability of the social economy.

The importance of predicting financial failure can play a crucial role in preventing companies from going bankrupt, so research studies on financial distress prediction are of great interest in accounting and corporate financial literature Sun and Li(2009). Early detection of financial failure and early intervention in this circumstance may minimize the adverse impacts of financial failure on both companies and investors Bulut and Şimşek(2018). In recent years, conventional approaches have been abandoned in the estimation of financial failure, modern approaches have been compared and studies have been conducted to determine which of the analysis techniques are more successful. The financial ratios utilized for predicting of financial failure in conventional approaches have begun to be analyzed more effectively by the analyses performed in modern approaches. The study's contribution to the literature, firstly, involves the aim of predicting financial distress by employing the machine learning methods of the modern approach and acquiring an idea regarding whether it can be used in distress prediction. Here, we provide distress and financial distress predictions for companies operating in the manufacturing industry in Turkey. Part 2 presents the descriptive statistics of the financial distress prediction and the comparative analysis among these companies. Part 3 introduces data, model features, and variables for financial distress analysis.

Part 4 consists of the empirical results of prediction performance, and consequently, conclusion statements and suggestions for future research studies. Altman (1968) entitled "Financial ratios discriminant analysis and the prediction of corporate bankruptcy", assessed the data of 66 manufacturing companies obtained over the period 1946 - 1965 by conducting ratio and discriminant analyses. The discriminant analysis proves extreme accuracy of the first group in correctly predicting bankruptcy for 94% of the cases, and 95% of the entire companies in the bankruptcy and non-bankruptcy groups assigned the actual group classifications are correct.

Akkaya, Demireli and Yakut(2009) studied the prediction of financial failures by employing the Artificial Neural Networks model. Within the scope of the study, 25 generally accepted financial ratios were determined from the financial statements of 53 enterprises operating in the Textile, Chemistry, Petroleum, and Plastic sectors registered in the ISE, and the data of these companies obtained over the period 1998-2007 were used. Li, Sun and Wu (2010) aimed to investigate the performance of BFP by utilizing the widely debated CART data mining technique in predicting financial failure. They obtained the financial ratios of 153 companies traded in the stock market in China. As a result of the analysis, they indicated the feasibility of employing CART in predicting financial failure. Chen and Guo (2010) employed the Gray Markov Forecasting Model for predicting a corporate financial crisis in their study. 5 financial ratios from 1998: Q1 to 2004: Q2 were selected to indicate whether or not the forecasting model could have accurately predicted the Z-Score value. They concluded that the Model could have accurately predicted Z-Scores, and therefore, was practically applicable.

Koyuncugil and Ozgulbaş(2012) tried to measure the financial insufficiency and financial distress aspects of SMEs using the Data Mining technique. According to the data of the Central Bank of the Turkish Republic in 2007, they generated a financial EWS model covering 7,853 SMEs. They categorized 7,853 SMEs into 31 risk profiles using the CHAID technique. Consequently, it was indicated that 31.4% of SMEs were experiencing financial distress. Maricica and Georgeta (2012) tested the financial ratios of 63 companies from different sectors in the Romanian stock market over the period 2009 - 2010 performing the t-test to test the importance of the difference between the averages for a series of financial measures for both groups of companies. As a result, it found certain differences among companies in terms of profitability and return, financial situation, capital structure, and indebtedness 2 years prior to failure. Yakut and Elmas (2013) analyzed the data of 140 manufacturing industry companies traded in the ISE over the period 2005 - 2008 by employing the Discriminant and Data mining methods in order to predict financial failure and found that data mining yielded better outcomes as a result of the analysis. Lakshan and Wijekoon (2013) employed a financial prediction model utilizing 15 financial ratios and logistic regression, using data obtained from 70 unsuccessful companies operated over the period 2002-2008 in Sri Lanka. It asserted that the predictive accuracy of the model was 77.86% 1 year before the failure. Besides, the predictive accuracy within 3 years prior to failure was over 72%. Therefore, they concluded that the model was robust in yielding correct outcomes up to 3 years prior to failure.Gepp and Kumar (2015) performed the Cox analysis and CART analysis to predict financial distress. For comparison, they predicted distress by performing discriminant analysis and logistic regression analysis. As a result, they stated that decision trees, especially the CART model, attain better classification accuracy than others. Geng, Bose, and Chen (2015) utilized data mining techniques in order to generate financial distress warning models along with 31 financial indicators and 3 distinct time windows in predicting the financial failure of 107 Chinese firms that were awarded the “special treatment” label over the years 2001-2008. As a result of the analysis, they asserted that the neural networks outperformed other classifiers, and were more accurate than multiple classifiers combined utilizing majority voting.

Kaygın, Tazegül, and Yazarkan (2016) predicted the financial success and failure situations of 143 manufacturing industry companies traded in Borsa Istanbul over the period 2010-2013 by performing the data mining technique and regression analysis using the annual data. They predicted the year 2012 as the most successful year with predictive power. Jabeur and Fahmi (2017) compared three statistical methods to be employed for predicting corporate financial distress. The assessment was made on a sample of 400 sound firms and 400 unsuccessful firms by performing discriminatory analysis and by employing random forest (RF) approach. They used 33 financial ratios over the period 2006 - 2008 in their study. In conclusion, they declared the RF approach superior. They argued that this approach yielded better classification results and provided better prediction accuracy. Ağırman (2018) analyzed 20 financial ratios of companies by employing the Artificial Neural Networks method to detect the most effective financial ratios in predicting the failure. It was determined that net working capital / total asset and capital adequacy ratios were crucial in all three periods. Hosaka (2019) employed the convolutionary neural network method to predict bankruptcy by utilizing the financial ratios of 2,168 companies traded on the Japanese stock exchange throughout the years 2002-2016. As a result of the analysis, they suggested that bankruptcy predictions over the trained network outperformed other methods.Lukason and Laitinen (2019) aimed at extracting firm failure processes (FFPs) utilizing failure risks and ranking the significance of failure risk factors at all phases of FFPs. The dataset was comprised of 1,234 bankruptcies, and they detected 3 FFPs. They emphasized that for the dominant FFP (73% of cases), the risk of failure increased quite shortly prior to the declaration of bankruptcy, the annual and cumulative productivity being the most significant risk factors for those phases of the entire FFPs, in which the probability of failure was highe than 50%. It was, however, revealed crucial implications for the research and application of bankruptcy prediction, especially for the determination of financial predictors.

2.Material Method

This study aims to determine the best financial failure prediction method upon comparing the methods by using 24 financial ratios of the financial data of 178 manufacturing companies trading in Borsa Istanbul over the period 2015-2019, employing the Machine Learning Methods to predict failure without experiencing financial difficulties 1- 5 years before the failure. Many criteria are used in the literature upon selecting the unsuccessful companies among the companies mentioned in the study. Orange software is used to test machine learning models. The failure criterion in our study involves the loss incurred by the company for two consecutive years. Financial ratios used in estimating financial failure are estimated using Excel software. The utilized financial ratios are shown below.

Table 1. Variables Obtained from Financial Statements

Independent Variables		Financial Ratios	Calculation
Liquidity Ratios	X1	Current Ratio	Current Assets/Current Liabilities
	X2	Acid-Test (Liquidity) Ratio	(Current Assets - Inventories)/ Current Liabilities
	X3	Cash Ratio	(Cash + Marketable Securities) / Short-Term Liabilities
Financial Structure Ratios	X4	Inventory to Total Assets Ratio	Inventories / Total Assets
	X5	Short-Term Liabilities to Equity Ratio	Short-Term Liabilities / Equity
	X6	Debt-to-Equity Ratio	Short- and Long-Term Liabilities / Equity
	X7	Fixed Assets to Equity Ratio	Fixed Assets / Equity
	X8	Current Assets to Total Assets Ratio	Current Assets / Total Assets
	X9	Short-Term Liabilities to Total Assets Ratio	Short-Term Liabilities / Total Assets
	X10	Long-Term Liabilities to Total Assets Ratio	Long-Term Liabilities / Total Assets

	X11	Financial Leverage Ratio	Short- and Long-Term Liabilities / Total Assets
Activity Ratios	X12	Cash Turnover Ratio	Net Sales / (Cash + Cash Equivalents)
	X13	Inventory Turnover Ratio	Cost of Goods Sold/Average Inventory
	X14	Current Assets Turnover Ratio	Net Sales / Current Assets
	X15	Asset Turnover Ratio	Net Sales / Average Total Assets
	X16	Equity Turnover Ratio	Net Sales / Average Equity
Profitability Ratios	X17	Gross Profit Margin	Gross Profit or Loss / Net Sales
	X18	Operating Profit Margin	EBIT / Net Sales
	X19	Net Profit Margin	Net Income / Net Sales
	X20	Return on Equity (ROE)	Net Income / Equity
	X21	Return on Capital Employed	EBIT / Total Liabilities
	X22	Return on Assets	Net Profits /Total Assets
	X23	Return on Assets (ROA)	EBIT / Total Assets
	X24	Coverage Ratio	Earnings before interest and taxes (EBIT) / Interest Expense
Dependent Variable	X25	Successful-Unsuccessful Companies	1-0

Source: Generated by the author as a result of the examination.

We select four different algorithms to compare conventional machine learning algorithms with deep learning models. These algorithms possess distinct mathematical backgrounds. Prior to employing each model for the analysis, certain preliminary processing is conducted as shown below. If a certain trend exists, the stationarity of the dataset should be realized by subtracting the data at time t-1 from those at time t. Certainlags may occur through getting the data ready for the time-series analysis. After employing the selected methodologies, the data are translated into the original scale. All datasets are divided into training (80%) and testing (20%) sets and the prediction models are evaluated. Model evaluation metrics on test data are based on performance. We utilized some evaluation metrics to achieve it. It is presented in Table 2.

Table 2. Evaluation Metrics

ANN Analysis Parameters	
Determined Parameters for the Analysis	Interpretation
Dataset Division	Training (80%) and Testing (20%) Datasets
Number of Variables	25
Number of Neurons in Hidden Layer	100
Activation function	ReLU
Number of Maximum Iterations	200
RF Analysis Parameters	
Determined Parameters for the Analysis	Interpretation
Dataset Division	Training (80%) and Testing (20%) Datasets
Number of Variables	25
Number of Trees	10
Maximum Number of Features to be included at Each Node Split	5
Lower Bound Criteria in Each Node	5
Depth Limit	3
SVM Analysis Parameters	
Determined Parameters for the Analysis	Interpretation

Dataset Division	Training (80%) and Testing (20%) Datasets
Number of Variables	25
Margin Width (C)	1
Hyperparameter (ϵ)	0.10
Error Tolerance	0.001
Iteration Limit	100
DT Analysis Parameters	
Determined Parameters for the Analysis	Interpretation
Dataset Division	Training (80%) and Testing (20%) Datasets
Number of Variables	25
Minimum Number of Samples at a Leaf Node	2
Minimum Number of Values in a Node that Must Exist Before a Split is Attempted	5
Maximum Depth	200
Percentage of Attaining Maximum Size	95%

1.1. Support Vector Machines (SVMs)

SVMs involve one of the frequently utilized algorithms.The Multi-Layer Perceptron (MLP) structure was firstly developed for the binary classification, before being extended for a regression. Let us suppose that a dataset $\{(x_1,y_2), \ldots\ldots, (x_l, y_l)\}$ is given, where each $xi \in R$ decision function is developed by the equation below Demirel, Cam and Ünlü (2021).

$$(x) = (x) + b$$

Regarding $w_i \in R$and $\} \in R$, where ϕ represents a nonlinear transformation from R^n to high-dimensional space. The magnitude of w must be minimized for ensuring (x) as flat as possible.

$$(w)=\frac{1}{2}\|\|w\|\|$$

Subject to the entire residuals assuming a value lower than ε;

$$(x_i) + b - yi \leq \varepsilon$$

It is supposed that this condition would be impossible for all datasets. Therefore, slack variables ξ^+andξ^- may be included to provide certain flexibility and revise the formulas.

$$(w) = \frac{1}{2}\|\|w\|\| + C\sum_i^n + + \xi^+ + \xi^-$$

Subject to:

$$y_i - (w\phi(x_i) + b) \leq \varepsilon + \xi^+$$

$$(w\phi(x_i) + b) - y_i \leq \varepsilon + \xi^-$$

$$\xi^+ \geq 0$$

$$\xi^- \geq 0$$

Here, C denotes a constant assigning a certain penalty value applied that lie outside the margin of ε and assisst to prevent overfitting. Consequently, we may estimate the loss function ignoring the error once ε exceeds or equals to the predicted value. Therefore, it may formulated as seen in Equation 5 below.

$$f(x) = \begin{cases} 0, & \text{if } w\phi(x_i) + b - y_i \leq \varepsilon | \\ lw\phi(x_i) + b - y_i \, | - \varepsilon, \text{otherwise.} (10) \end{cases}$$

The optimization problem may be solved in binary form for mathematical convenience.

1.2. Artificial Neural Network (ANN) Algorithm

Multi-Layer Artificial Neural Network Algorithm - also known as MLP – refers to as one of themachine learning methods employed to extract hidden nonlinear relationships out of data. The ANN includes certain layers [28]. Feed forward neural networks involves the mechanism of data samples entering the network through the input layers, and values being transmitted to neurons at the consecutive layer. Nonetheless, back propagation involves the mechanism of obtaining the values from the input layer into the output layer for optimizing the weights. The output of the neurons is estimated as follows(Kohonen 1988; Lippmann 1988).

$$o = y_n^l = w^T x + b$$

Here, w^T denotes the connection weights. Activation functions transform the values of all nodes. The sigmoid function, converting the value to 1 or 0, is chosen.

$$(\boldsymbol{x}) = \frac{1}{1 - e^{-(w^T x + b)}}$$

For minimizing the errors, the weights must be revised according to Equation.

$$D = \{(x_1, t_1), (x_2, t_2), \ldots, (x_d, t_d), \ldots, (x_m, t_m)\}$$

$$[\vec{w}] = \frac{1}{2} \sum_{d \in D} (\boldsymbol{td} - \boldsymbol{od})$$

To set w_i, $w_i := w_i + \Delta w_i$, the partial derivative procedure must be used for all w_i as seen in Equation.

$$\Delta w_i = -\eta \frac{\partial E}{\partial wi}$$

Here, $-\eta$ denotes the learning rate, whereas Δw_irepresents the adjustment value. We may sum up the adjustment rules as seen in Equation.

$$\Delta w_i = -\boldsymbol{\eta} \sum_{d \in D} (t_d - o_d \boldsymbol{d} \in \boldsymbol{D}) x_{id}.$$

It should be noticed that, a single neuron would exist at the MLP model's output layer.

2.3. Random Forest (RF) Algorithm

RFC is a collection of DT classifiers that constitute large classes. It ensembles the collections of unrelated trees and each tree's prediction to assign a class using majority voting(Aria et al., 2021;

Bhattacharyya et al., 2011; Dietterich, 2000). It utilizes a random subset of the full training set to train all trees independently and splits all nodes through a randomly chosen feature without pruning(Altendrof et al., 2005; Azar et al., 2014).

$$H(x) = \arg max_{y}(\sum_{i=1}^{n} I(hi\ (x) = Y\ ))$$

where,

$h_i$denotes the single trees of the model,

Y represents target output, and

I stand for the indicator function.

RF algorithms are thought to be more appropriate for fraud detection than other classifiers.

2.4. Decision Trees (DTs)

DTC is illustrated by a tree-like figure to predict an eventual decision (Breiman, 1996; Cody et al., 2015). Information entropy and Gini impurity are 2 regular metrics that have been utilized to split the classification. In summary, Gini impurity refers to the probability that a randomly selected dataset may be mislabeled. Entropy functions in a similar manner. The attribute of the minimum entropy is chosen to constitute a DT node. Then recursive partitioning is applied to the other nodes to finalize the DT. Entropy may be described by the equation below(Mitchell, 1997; Song and Lu, 2015):

$$S= \sum_{i}^{c} =1\ (p_i - log_2 p_i)$$

Here,

S denotes entropy,

c presents the number of classes and,

pi stands for the most frequent probability of the ith class,

DTCs are simplier to interpret than most of the other models,

3. *Research Findings and Discussion*

The accuracy measures are presented below.

Table 3. Results of MLP, SVM, RF, and DT models

	ANN					SVM				
	AUC	CA	F1	Pre.	Rec.	AUC	CA	F1	Pre.	Rec.
T-1	0.937	0.916	0.906	0.918	0.916	0.902	0.865	0.828	0.884	0.865
T-2	0.894	0.882	0.884	0.887	0.882	0.865	0.848	0.835	0.831	0.848

T-3	0.871	0.888	0.886	0.886	0.888	0.929	0.848	0.833	0.854	0.848
T-4	0.921	0.831	0.808	0.844	0.831	0.891	0.798	0.754	0.825	0.798
T-5	0.937	0.916	0.906	0.918	0.916	0.893	0.843	0.840	0.838	0.843
	RF					DT				
	AUC	CA	F1	Pre.	Rec.	AUC	CA	F1	Pre.	Rec.
T-1	1.000	0.994	0.994	0.994	0.916	0.985	0.989	0.989	0.989	0.989
T-2	0.930	0.876	0.883	0.896	0.876	0.748	0.871	0.874	0.880	0.871
T-3	0.943	0.888	0.890	0.897	0.888	0.847	0.831	0.834	0.839	0.831
T-4	0.894	0.854	0.838	0.864	0.854	0.672	0.831	0.817	0.828	0.831
T-5	0.897	0.848	0.856	0.880	0.848	0.747	0.764	0.773	0.790	0.764

AUC corresponds to the area below the ROC curve ranging between 0 and 1. If the AUC value equals to 0, then all predictions are wrong. The correct positive ratio briefly indicates how many of them we predict positively if the situation is actually positive.The false positive rate indicates the number of them predicted as positive (also called false alarms) when the situation is actually negative.In other words, it reveals the extent to which it may distinguish positive classification from negative classification. Besides, the higher the AUC, the better the performance of the model in figuring out successful and unsuccessful firms. CA is known as the classification accuracy score. In multi-labeled classification, this function calculates subset accuracy. The F1-score comes into play in balancing Precision and Recall. An F1-score can be interpreted as a weighted mean of precision and recall where it equals to 1 at the best, and 0 at the worst. In the multi-class and multi-labeled case, this is the mean of each class' F1-score, with the weighting based on the parameter. Precision refers to as the division of the number of true positives to the number of false positives. Precision is the classifier's ability not to intuitively label a negative example as positive. It involves the number of correctly predicted examples among all of the positive examples. The best and the worst values are 1 and 0, respectively. Recall, the division of the number of true positives to the number of false negatives, referring to as the classifier's ability to intuitively detect all negative examples. The best and the worst values are 1 and 0, respectively (Noyan, 2020).

Upon examining the F1 scores of the companies, it is seen that the machine learning model yields the following resultsfrom the highest score to the lowest: the predictive powers of the RF method (99.4%), the DT method (98.9%), and the ANN method (88%) for 1 year before failure; the predictive powers of ANN method (88.4%), the RF method (88.3%), the DT method (87.4%), and the SVM method (83.5%) for 2 years before failure; the predictive powers of the RF method (89%), the ANN method (88.6%), the DT method (83.4%), and the SVM method (83.3%) for 3 years before failure; the predictive powers of the RF method (83.3%), the DT method (81.7%), the ANN method (80.8%), and the SVM method (75.4%) for 4 years before failure; the predictive powers of the ANN method (85.8%), the RF method (85.6%), the SVM method (84%), and DT method (77.3%) for 5 years before failure. The best predictive power is seen to be achieved by RF (random forest) method, 1 year before failure (T-1); ANN (artificial neural networks) method, two years before failure (T-2); again RF (random forest) method, 3 years before failure (T-3); again RF (random forest) method, 4 years before failure (T-4); and ANN (artificial neural networks) method, 5 years before failure (T-5).

Table 4. The ANN Classification Matrix

	Prediction			
Actual Value	T-1	0	1	∑
	0	22	9	31
	1	12	135	147
	∑	34	144	178
	Prediction			
Actual Value	T-2	0	1	∑
	0	22	9	31
	1	12	135	147
	∑	34	144	178
	Prediction			
Actual Value	T-3	0	1	∑
	0	36	12	48
	1	8	122	130
	∑	44	134	178
	Prediction			
Actual Value	T-4	0	1	∑
	0	20	28	48
	1	2	128	130
	∑	22	156	178
	Prediction			
Actual Value	T-5	0	1	∑
	0	28	14	42
	1	11	125	136
	∑	39	139	178

Table 5.The RF Classification Matrix for T-1

	Prediction			
Actual Value	T-1	0	1	∑
	0	30	1	31
	1	0	147	147
	∑	30	148	178
	Prediction			
Actual Value	T-2	0	1	∑
	0	27	4	31
	1	14	133	147
	∑	41	137	178
	Prediction			
Actual Value	T-3	0	1	∑
	0	41	7	48
	1	16	114	130
	∑	47	121	178
	Prediction			
Actual Value	T-4	0	1	∑
	0	25	23	48
	1	2	128	130

Actual Value				
	∑	27	151	178
	Prediction			
	T-5	0	1	∑
	0	36	6	42
	1	21	115	136
	∑	57	121	178

Table 6.The SVM Classification Matrix for T-1

Actual Value	Prediction			
	T-1	0	1	∑
	0	7	24	31
	1	0	147	147
	∑	7	171	178
Actual Value	Prediction			
	T-2	0	1	∑
	0	12	19	31
	1	8	139	147
	∑	20	158	178
Actual Value	Prediction			
	T-3	0	1	∑
	0	24	24	48
	1	3	127	130
	∑	27	151	178
Actual Value	Prediction			
	T-4	0	1	∑
	0	13	35	48
	1	1	129	130
	∑	14	164	178
Actual Value	Prediction			
	T-5	0	1	∑
	0	26	16	42
	1	12	124	136
	∑	38	140	178

Table 7.The DT Classification Matrix for T-1

Actual Value	Prediction			
	T-1	0	1	∑
	0	30	1	31
	1	1	146	147
	∑	31	147	178
Actual Value	Prediction			
	T-2	0	1	∑
	0	22	9	31
	1	14	133	147
	∑	36	142	178
Actual Value	Prediction			

T-3	0	1	∑
0	36	12	48
1	18	112	130
∑	54	124	178

Actual Value

Prediction

T-4	0	1	∑
0	24	24	48
1	6	124	130
∑	30	148	178

Actual Value

Prediction

T-5	0	1	∑
0	27	15	42
1	27	109	136
∑	54	124	178

Upon considering the classification matrixes, in general, it is seen that all the methods used up to one year prior to failure attain extremely good classification ability. Upon going backward from the year of failure, it is understood that the model is at an acceptable level in financial terms, even if the predictive power of the model weakens in classifying successful and unsuccessful companies.

4. Results

Failure prediction models are generated all over the world to predict the failure of companies that are of high importance at both micro and macro levels in terms of countries and take the necessary precautions prior to filing for bankruptcy. This subject constitutes a quite popular field of study for both financial stakeholders and academicians. These studies have been classified by employing univariate statistical methods and multivariate statistical methods since the early 1900s. In recent years, machine learning models that mimic the human brain have become quite common in failure prediction.

Upon considering various prediction models ever established, one would claim that the most appropriate prediction model cannot be developed or a consensus cannot be reached on this issue. Therefore, it is aimed to detect the most appropriate method by comparing the failure prediction results of all methods by using the five-year financial statement data of BIST industrial companies by employing machine learning methods, also known as modern methods. ANNs, DTs, SVMs, and RF methods are employed to establish financial failure prediction models. 24 generally accepted financial ratios of 178 companies traded in the BIST manufacturing industry over the period 2015-2019. And prediction models are generated for companies up to 5 years before the failure. Moreover, as a failure criterion, companies that declared a loss for two consecutive financial years are considered unsuccessful, whereas companies that did not incur any loss are considered successful.

Upon considering the elements that render the study different from other studies, it is the sector, dataset, study periods, and prediction analysis conducted on companies that continue their activities but declare profit and loss repeatedly. Again, it is the employment of four different machine learning methods and the comparison of these methods among themselves. Comparing these models by establishing a prediction model up to 5 years before failure is also to generate the best prediction model by comparing the determined failure criteria with the failure and success situations throughout the same period on a separate firm basis.

It is seen that the predictive power of machine learning methods in classifying successful and unsuccessful companies decreases as we go back from the year of failure. Upon considering it in financial terms, it is seen that machine learning models have quite good predictive and classification power and these rates are at an acceptable level.As a result, it is detected in this study that, in the prediction modeling generated by machine learning methods according to the criteria of incurring loss or earning profit for two consecutive years, which is frequently used in the literature for the companies in our dataset, machine learning methods have an acceptable predictive power for the companies up to five years prior to becoming successful or unsuccessful. It is concluded that stakeholders of the companies such as the government, funders, investors, company management, and company employees may benefit from the prediction models generated in this study in order to analyze the current situation of the company and to solve the problems identified in the analysis, to make short-and long-term plans for the future, as well as effective decisions. In addition to this study on financial failure prediction, the effectiveness of machine learning methods can be compared by using independently audited financial statements, by developing prediction models for other sectors or among sectors.

Conflicts of Interest

No conflict of interest was declared by the authors.

References

Aksoy, B. (2018). "İşletmelerde finansal başarısızlık tahmininde very madenciliği yöntemlerinin karşılaştırılması: Bist'de bir uygulama", Yayımlanmamış Doktora Tezi, Erciyes Üniversitesi, Kayseri.

Akgün, A., "Firmalarda finansal başarısızlığın tahmini ve İstanbul menkul kıymetler borsası'nda bir uygulama", Yayımlanmamış Doktora Tezi, Selçuk Üniversitesi, Konya. (2013).

Asquith, P., Gertrier, R., & Scharfstein D. (1991). "Anatomy of financial distress: An examination of junk-bond issuers", National Bureau of Economic Research Massachusetts Avenue Cambridge, 3942:1-5.

Altman, E. I. (1968). "Financial ratios discriminant analysis and the prediction of corporate bankruptcy", *The Journal of Finance*, 23(4): 589-60.

Akkaya, G. C., Demireli E., & Yakut Ü. H. (2009). "İşletmelerde finansal başarısızlık tahminlemesi: Yapay sinir ağları modeli ile İMKB üzerine bir uygulama", Eskişehir Osmangazi Üniversitesi Sosyal Bilimler Dergisi, 10(2):187-216.

Ağırman, E., (2018). "Finansal sıkıntı göstergeleri: Bist'te işlem gören imalat sanayi firmaları üzerine bir araştırma", *Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 32(2):403-426.

Aria M., Cuccurullo C., & Gnasso A. (2021). "**A comparison among interpretative proposals for random forests",** *Machine Learning with Applications*, 6.

Altendrof, J., Brende, P., & Lessard, L. (2005). "Fraud detection for online retail using random forests", Technical Report.

Azar A.T., Elshazly H.I., Hassanien A.E., & Elkorany A.M. (2014). "A random forest classifier for lymph diseases", *Computer Methods and Programs in Biomedicine*, 113(2):465-473.

Breiman, L. (2001). "Random forests", In Machine Learning, 45(1): 5-32.

Beaver, W. H. (1966). “Financial ratios as predictors of failure”. Empirical Research in Accounting: Selected Studies, *Journal of Accounting Research*, 4:71-111.

Bulut, E., & Şimşek İ. Ş. (2018). “Financial failure estimation with logistic regression model: a study on technology sector companies treated in Bıst”, Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi , 6:177-183.

Bhattacharyya S., Jha S., Tharakunnel K., & Westland J.C. (2011). “**Data mining for credit card fraud: A comparative study”,** *Decision Support Systems*, 50(3):602.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2010). “Predicting financial distress and the performance of distressed stocks”, *Journal of Investment Management* 9(2):14-34.

Chen, W. S., & Du, Y. K. (2009). “Using neural networks and data mining techniques for the financial distress prediction model”, *Expert Systems With Applications*, 36: 4075.

Chen, L. H., & Guo, T. Y. (2010). “Forecasting financial crises for an enterprise by using the grey markov forecasting model”, *Qual Quant*, 45:911–922.

Cody C., Ford V., & Siraj A. (2015). **“Decision tree learning for fraud detection in consumer energy consumption”,** IEEE 14th international conference on machine learning and applications, 14:1175-1179.

Demirel, U., Çam, H., & Ünlü, R. (2021). “Predicting stock prices using machine learning methods and deep learning algorithms: The sample of the İstanbul stock exchange”, *Journal of Science*, 34(1):63-82.

Dietterich T.G. (2000). “Ensemble methods in machine learning”, *International workshop on multiple classifier systems*, Springer, Berlin, Heidelberg, 1-15.

Gepp, A., & Kumar, K. (2015). “Predicting financial distress: a comparison of survival analysis and decision tree techniques”, *Procedia Computer Science*, 54:396-404.

Geng, R., Bose, I., & Chen, X. (2015). “Prediction of financial distress: An empirical study of listed chinese companies using data mining”, *European Journal of Operational Research*, 241:236–247.

Hosaka, T. (2019). “Bankruptcy prediction using imaged financial ratios and convolutional neural networks”, *Expert systems with applications*. 117:287-299.

Jabeur, S. B., & Fahmi, Y., (2017). “Forecasting financial distress for french firms: a comparative study”, Empir Econ, 54:1173–1186.

Kaygın, C. Y., Tazegül, A., & Yazarkan, H. (2016). “İşletmelerin finansal başarılı ve başarısız olma durumlarının very madenciliği ve lojistik regresyon analizi ile tahmin edilmesi”, *Ege Akademik Bakış Dergisi*, 16:147-159.

Kohonen, T. (1988). “An introduction to neural computing”, *Neural Networks*, 1(1):3-16.

Koyuncugil, A. S., & Ozgulbaş, N. (2012). “Financial early warning system model and data mining application for risk detection”, *Expert Systems With Applications*, 39(6):6238-6253.

Lanskman, A. M. I., & Wijekoon, W. M. H. N. (2013). “The use of financial ratios in predicting corporate failure in srilanka”, *GSTF Journal on Business Review*, 2(4):37-43.

Li, H., Sun, J., & Wu, J., (2010). "Predicting business failure using classification and regression tree: An empirical comparison with popular classical statistical methods and top classification mining methods", *Expert Systems with Applications*, 37:5895-5904.

Lippmann, R. P. (1988). "An introduction to computing with neural nets", Artificial Neural Networks: *Theoretical Concepts*, 36–54.

Lukason, O., & Laitinen, E. K. (2019). "Firm failure processes and components of failure risk: an analysis of european bankrupt firms", *Journal of Business Research*, 98: 380-390.

Maricica, M., & Georgeta, V. (2012). "Business failure risk analysis using financial ratios", *Procedia - Social and Behavioral Sciences*, 62:728–732.

Mselmi, N., & Lahiani, A., Hamza, T. (2017). "Financial distress prediction: The case of french small and medium-sized firms", *International Review of Financial Analysis*, 50:67-80.

Mitchell T. M. (1997). "Artificial neural networks", Machine Learning, 45:81-127.

Noyan, M. (2020). 15 Eylül 2021 tarihinde https://medium.com/deep-learning-turkiye/regresyon-ve-s%C4%B1n%C4%B1fland%C4%B1rmada-hata-metrikleri-143a40c6b656 adresinden erişilmiştir.

Onyırı, S. (2014). "Predicting financial distress using Altman's Z-score and the sustainable growth rate", Submitted to North Central University, Prescott Valley, Arizona.

Pindado, J., Rodrigues, L., & Torre, C. D. L., (2008). "Estimating financial distress likelihood", *Journal of Business Research*, 61(9):995-1003.

Song Y., & Lu Y. (2015). "**Decision tree methods: Applications for classification and prediction",** *Shanghai Arch Psychiatry*, 27(2):130.

Sun, J., & Li H. (2009). "Financial distress early warning based on group decision making", *Computers& Operations Research*, 36(2009), 885–906.

Sun, J., & Li, H. (2012). "Financial distress prediction using support vector machines: ensemble vs. individual", *Applied Soft Computing*, 12(8):2254–2265.