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A New Approach to Predict Financial Failure: Classification and Regression Trees (CART)

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The increase of competition, economic recession and financial crises has increased business failure and depending on this the researchers have attempted to develop new approaches which can yield more correct and more reliable results. The classification and regression tree (CART) is one of the new modeling techniques which is developed for this purpose. In this study, the classification and regression trees method is explained and tested the power of the financial failure prediction. CART is applied for the data of industry companies which is trade in Istanbul Stock Exchange (ISE) between 1997-2007. As a result of this study, it has been observed that, CART has a high predicting power of financial failure one, two and three years prior to failure, and profitability ratios being the most important ratios in the prediction of failure.

Keywords: business failure, financial distress, prediction, classification and regression trees (CART)

Introduction

During the past decades there have been significant changes observed in both national and international environment in which businesses operate. Economic, political, legal, social, and industrial circumstances have changed rapidly, and businesses found themselves in a highly competitive climate. Whilst businesses that could keep up with the changes can survive, others that are unable to withstand the severe competition around them and to adapt to their environment incurred to financial failures which may well lead all the way to bankruptcy. It is seen that business failures are encountered especially during times of economic recession, high inflation, and lower growth rates as well as economic and financial crises. It has been witnessed that due to the recent economic crisis that has affected our country along with many others, many industries have been highly influenced, production has decreased, and many businesses have closed down, failing in their attempt to cope with this crisis.

Business failure is a general term and a situation in which a firm can not pay lenders, preferred stock shareholders, suppliers or the firm legally bankrupt (Lin, Yeh, & Lee, 2011). Financial failure leads to a decrease in profitability and equity problems in businesses (Türko, 1999). A business failure may happen as a result of poor management skills insufficient marketing and lack of ability to compete with other similar businesses (Wu, 2010).

The negative effects of financial failure are not only a concern of the groups with a direct relationship with

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businesses such as stockholders, owners, managers, bondholders, or creditors, but also have an influence on economic prosperity and employment. For this reason, financial failure has been an issue which requires close attention from the perspective of national economies and global economy. Determining financial failure as a rather serious matter, utilizing models built on objective criterion, and using it as a measurement tool becomes quite important not only in terms of enabling businesses to take precautions in advance, but also with regard to resource allocation, employment and investment levels which have an impact on a country's economy at a national level.

The increasing importance of financial failure, from both micro and macro perspectives, has forced researchers to find ways to develop early warning indicators, which enable the prediction of the failure in advance. Single and multivariate statistical models are being used for this purpose. The most important single variable statistical models are simple regression analysis, single discriminant analysis, and the Markov chain method. The multiple discriminant model, logistic regression model, and probit regression model are the main multiple variable statistical models used to predict financial failure. Increased competition and the increase in failed businesses as a result of circumstances related to economic crisis have led researchers to conduct financial failure prediction research that is more reliable and which can provide more accurate results by developing new models. One of the models developed for this purpose is the classification and regression trees method. The CART method has been used in studies that were conducted in other countries with considerably high prediction values attained in financial failure prediction. However, no such use of this particular method has been observed in Turkey. Therefore, in this study, the CART method will be explained and the accuracy of financial failure will be tested on industrial businesses with stocks listed on the Istanbul Stock Exchange (ISE) between 1997 and 2007.

Classification and Regression Trees Method in Prediction of Financial Failure

An Overview of Classification and Regression Trees

The CART method is based on decision trees. A decision tree is a predictive model. The decision trees method has been one of the most important classification and prediction methods used in recent years. CART is one of the most commonly used decision tree methods (Koyuncugil & Özgülbaş, 2008).

CART is a nonparametric statistical methodology developed for analyzing classification issues either from categorical or continuous dependent variables. If the dependent variable is categorical CART produces a classification tree. CART's major goal is to produce an accurate set of data classifiers by uncovering the predictive structure of the problem under consideration (Breiman, Friedman, Olshen, & Stone, 1993).

The CART method has many advantages compared to other prediction methods which are utilized to predict financial failure. These advantages can be categorized as follows:

(1) CART makes no distributional assumptions of any kind, either on dependent or independent variables. No variable in CART is assumed to follow any kind of statistical distribution;

(2) The explanatory variables in CART can be a mixture of categorical, interval and continuous;

(3) CART has a built-in algorithm to deal with the missing values of a variable for a case, expect when a linear combination of variables is used as splitting rule;

(4) CART is not at all affected by outliers, collinear ties, heteroscedasticity or distributional error structures that affect parametric procedures;

(5) CART has the ability to detect and reveal interactions in the data set;

(6) CART's effectively deals with higher dimensionality, that is, from a large number of variables submitted for analysis, it can produce useful results using only a few important variables (Yohannes & Hoddinott, 1999);

(7) An important weakness of CART is that it is not based on a probabilistic model. There is no probability level or confidence interval associated with predictions derived from using a CART tree to classify a new set of data (Yohannes & Hoddinott, 1999).

Use of the Classification and Regression Trees Method in Prediction of Failure

The most important disadvantage of statistical models used in the prediction of financial failure is the inability to ensure the homogeneity in the data set in situations when the analyzed sample is too large. This problem is eliminated with the CART analysis which utilizes a compelling binary recursive algorithm splitting the data set into sub nodes and ensuring homogeneity (Kayrive & Boysan, 2007).

Classification trees is a statistical methodology that is improved nonparametric to analyze and to estimate the values of dependent variables. Even if the data set is very complex, the variables that affect dependent variable and the importance of these variables in the model can be done by visual presentation without setting a complex mathematical model. CART analysis is from of binary recursive partitioning (Bevilacqua, Braglia, & Montanari, 2003). A tree sample model can be given in Figure 1.

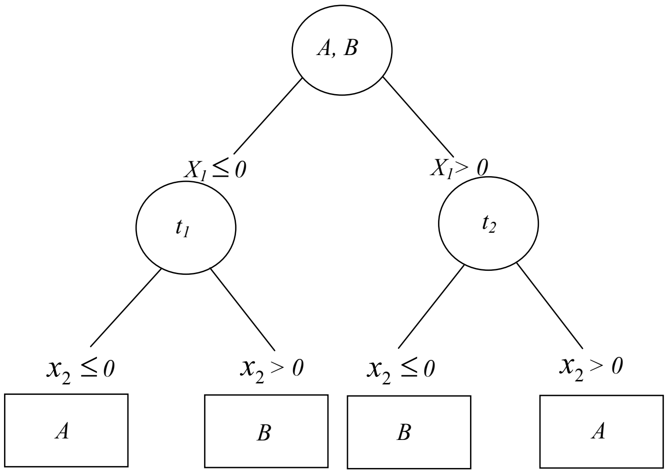

Figure 1. Sample tree model.

In the tree sample model, *A* and *B* are dependent variable groups, X_1 and X_2 are independent variables, t_1 and t_2 can be defined as a node. The decision points called node in tree models. The main purpose here is to reach more homogeneous subgroups by dividing into binary recursive partitioning from the beginning of node and to define the classification of dependent variable in decision points (Bremmer & Taplin, 2002).

While a classification tree is built, independent variables that experiment units in the node consist, and hypothesize the whole probable variables as criterion in spaces, which define the combinations of variables with each other, the whole probable separation is determined. For each possible separation, the separation which has got the maximum appropriateness degree is determined by counting the appropriateness degree of separation with the help of separation function. Separation function is shown in the diagram below as mathematical.

$$\Delta(\delta(t))=i(t)-P_L.i(t_L)-P_R.i(t_R) \quad (1)$$

Here, from P_L and P_R, t nodes give the ratio of experiment units which are assigned to left and right child node in a row; *i(t)* gives impurity measurement of *t* node and $i(t_L)$ and $i(t_R)$ give impurity measurement of left and right child node in a row (Breiman & Friedman, 1993).

After the appropriateness degree of each probable separation is counted with the help of separation function, *δ(t)* separation which has got maximum appropriateness degree is chosen as the best separation and *t* node is separated by this way. With the criterion that makes the best separation being applied to *t* node, the most appropriate class can be estimated for each of the left and right child nodes. This practice is repeated for each node which will appear then from the beginning of root node. At the end of the tree construction, the tree which is obtained at the end of the tree construction is called maximal tree. As maximal tree defines Learning Sample perfectly, every independent variable which is added decreases the faulty classification ratio. In this case, maximal tree serves the more over fitting estimation model than necessary for Learning Sample. However, maximal trees which are excessive harmonious to Learning Sample don't provide a good estimation when a different data set is discussed (Breiman, Friedman, Olshen, & Stone, 1993).

For the solution of these problems that maximal tree exposed in practical, the maximal tree should be pruned that is to say the smaller tree which is exposed from maximal tree should be chosen. The prunings of maximal tree expose series of the smaller tree and from this series, optimal tree is chosen. In this level, independent variables which explain the dependent variable the best have been determined. Cost-complexity pruning method which is used for selection of optimal tree provides the balance between faulty classification ratio and tree's complexity; it is expressed mathematically in this way:

$$R_\alpha^{(T)} = R(T) + \alpha T \tag{2}$$

Here, $R_\alpha^{(T)}$ shows cost-complexity measurement; *R(T)* shows the fault ratio which is counted for T tree; *T* shows the number of node on the tree and *α* shows punishment coefficient ($\alpha \geq 0$) which is determined for every terminal node (Put, Questier, Coomans, Massart, & Heyden, 2003).

According to cost-complexity pruning method, maximal tree is pruned until cost-complexity measurement reaches minimum value and then optimum tree is obtained. The increase of a value in cost-complexity measurement causes less terminal node to be located in optimal tree. In other words, the more *α* value increases, the more the pruning increases. *R(T)* which is located in cost-complexity measurement can be given Resubstitution Estimate, Test Sample Estimation, Cross Validation Test (StatSoft. classification and regression trees).

Literature Review

The CART method is often used in the fields of medicine, psychology, and biostatistics. However, it is a relatively new method in financial failure prediction. Therefore there are only a limited number of studies in which this method in this particular area has been used.

Chen, Marshall, Zhang, and Genesh (2006) used the CART method along with discriminant analysis, logistic regression analysis, and artificial neural networks in financial failure prediction. In their study, they aimed at predicting financial success or failure two years prior to failure. They used a sample consisting of failed and successful businesses listed in the Shanghai Stock Exchange. In order to conduct the analysis, they selected 56 failed and 739 successful business for the prediction sample, and 89 failed and 940 successful for the test sample. In this study, businesses that demonstrated continuous losses and which had their shares de-listed were considered unsuccessful. For the businesses involved, 34 financial ratios were calculated in the analysis. Following the analysis, the accuracy ratios of failure business were found to be 58.43% by disciminant analysis, 87.64% by logistic regression, 93% by artificial neural networks and 74.53% by CART. On the other hand, the accuracy ratios of both failure and successful business were found to be 77.67% by disciminant analysis, 87.37%

by logistic regression, 77.84% by artificial neural networks and 92.87% by CART.

Lee, Chiu, Chou, and Lu (2006) aimed to explore the performance of credit scoring using logistic regression, artificial neural networks, CART, and multivariate adaptive regression splines (MARS) methods. In the study, credit information acquired from a local bank in Taiwan, and data that belonged to 4000 clients have been examined. They used the credit status (good-bad) as the independent variable in their analysis. The dependent variables consisted of variables such as gender of the client, age, marital status, educational level, occupation, resident status, annual income and loan amount. Following the analysis, the failed loans prediction ratios were found to be 70.9% using the logistic regression method, 73.85% using the artificial neural networks, 77.95% using the CART method and 77.75% using MARS method.

Lee (2008) calculated the prediction performance of the financial failure of each method by employing the logistic regression, artificial neural networks, the classification and regression trees, C5.0 and genetic algorithm decision trees. He took 55 failed and 110 successful businesses operating in Taiwan and determined eight different ratios belonging to the businesses as independent variables. He used 33 out of 55 unsuccessful businesses as learning sample, 22 as test sample; 67 out of 110 successful businesses as learning sample and 43 as test sample in his effort to perform the analysis. The CART method, C5.0 and genetic algorithm decision trees method predicted financially failed businesses a year in advance by ratios of 50%, 77.27%, and 92.91% respectively. All three methods of decision trees models correctly predicted financial failure with a high degree of accuracy.

Use of the Classification and Regression Trees Method in Failure Prediction of Industry Companies Listed on the Istanbul Stock Exchange

Sample Selection

The data referred in this study are based on companies of which the stocks are listed on the ISE between the years of 1997 and 2007. Firms in the sectors of service, finance, energy, transportation, holding, trade, and IT are excluded from the research sample as the statement of accounts of these companies and independent variables obtained using these statements are significantly different. The successful and failed firms included in the study were determined in light of the following criteria. The firms were identified as failed if they filed bankruptcy or had negative equity, made losses for three years in a row, listed in the watch list companies market because of financial difficulties and had stocks delisted by the ISE board of directors.

The balance sheet and income statements of enterprises are examined for the period between 1977 and 2007. Following the analysis, companies with negative equity and companies that had made losses for 3 years in a row were included in the research as financially failed companies. Firms that filed bankruptcy, listed in the watch list companies market, or delisted were identified by scanning through the information provided in the website of ISE (www.imkb.gov.tr). The third year of a three year trend for companies, the year in which they filed bankruptcy, they had negative equity and they listed in the watch list companies market was selected as the year of failure. However, companies demonstrating success from a financial perspective were selected as those which did not fit into any of the categories listed above.

In light of the scope and the criteria stated, 70 failed firms are identified and included in the sampling. Subsequently, by taking the assets, sector, and year of failure into consideration, 70 successful businesses were added to the sample and matched against the failed businesses. Businesses with success in the year of "*t*", and the sector of "*x*" were first determined in order to match them with the businesses that failed in the same year and sector, and businesses with the highest asset size were matched against the closest failed businesses.

Selection of Independent Variables

The independent variables used in the models of this study are composed of financial ratios that are widely used in financial failure prediction and are considered significant in the prediction of failure. In the analyses, 29 ratios in the categories of liquidity, financial structure, turnover and profitably are applied. Financial ratios used are presented in Appendix.

Twenty nine different ratios determined as independent variables were calculated taking in consideration annual balance sheet and income statements for 1, 2, and 3 years prior to failure time for both successful and failed companies. The analyses are conducted using the Statistic® 7.0 programme, with Gini index being used as the division criteria and a tenfold cross validation test being preferred as an accuracy prediction of the classification tree to determine the optimal tree following pruning. Prior probability is considered equal (0.5) as the number of businesses in each group was the same.

Findings of the Study

The findings of the study in predicting the financial condition of 140 businesses included in our data set one, two and three years prior to failure, using the CART can be summarized under three headings.

Financial failure prediction one year prior to failure with the CART method. The financial ratios of both successful and failed businesses' for the year prior to the year in which they had been determined successful or unsuccessful are used as independent variables in the CART method in an attempt to determine, one year in advance, which businesses would be financially unsuccessful.

In the first stage of the CART analysis, the 29 independent variables consisting of financial ratios of 140 firms are analyzed and a maximal tree indicating an elaborate correlation between variables is constructed. After the construction of the maximal tree, a new tree is constructed by gradually pruning it from bottom to top, beginning from the very bottom child node ensuring that the new tree has fewer nodes and a higher misclassification rate than the previous tree. The optimal tree, which assures the best balance between the decrease in the number of nodes with the increase in rates of misclassifications after the process of pruning using the tenfold cross validation test, is presented in Figure 1.

In this newly constructed tree, the two squares at the far bottom represent terminal nodes that are homogenous groups, and the square at the top corresponds to child node that is heterogeneous. Within the nodes, the belonging of the node to either classification (financially successful or failed) is stated. Within each node, the number of test companies is denoted as N placed on the right top corner and the node number as ID located on the left top corner. In addition, classes of each test companies within each node are presented in a bar graph and the class assignment of that particular node is stated (see Figure 2).

According to the optimal tree constructed, the net income/total liabilities + equity is the most important variable due to developing the best split, with income/total liabilities + equity ≤ 0.000515 indicating a failed business, and income/total liabilities + equity > 0.000515 indicating a successful one. In light of this criterion, the success of the CART predicting businesses' financial situation one year in advance is shown in Table 1.

As shown in Table 1, the CART method attained 92% accuracy in prediction failure of 65 out of 70 businesses one year prior to failure. Sixty-eight out of 70 businesses appear to be predicted accurately and the prediction rate of successful businesses is 97%. In more general terms, the classification rate of both successful and failed businesses one year prior is 95% by the model.

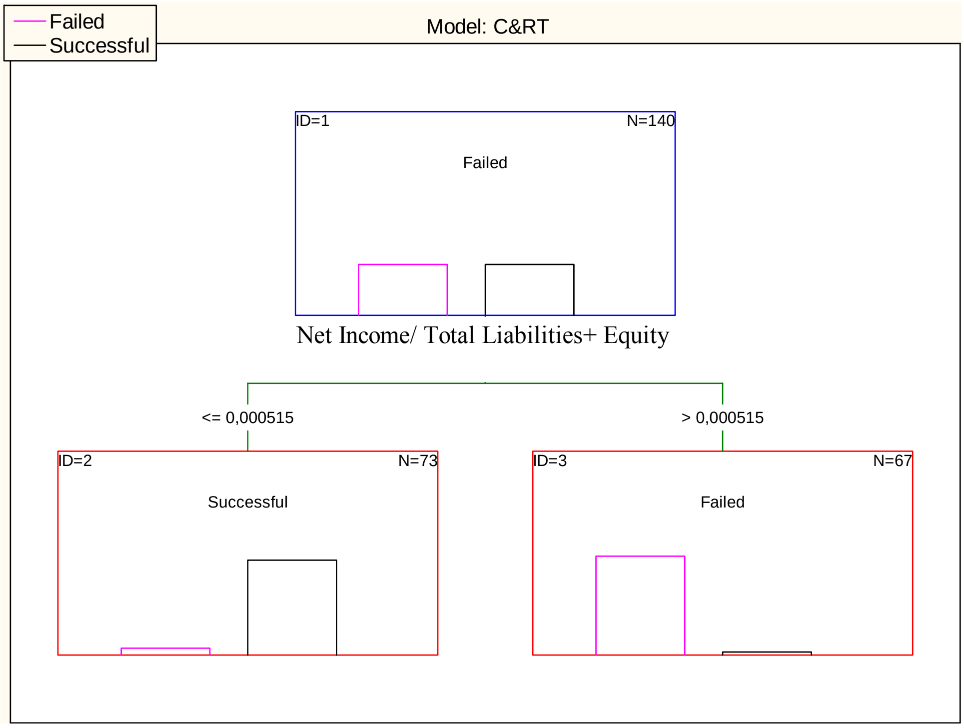

Figure 2. Optimal tree constructed for financial failure prediction one year in advance.

Table 1

The Accuracy of CART Method in Prediction One Year Prior to Failure

Total sample	Number	Predicted group membership		Accuracy in prediction (%)
		Failed	Successful	
Failed	70	65	5	92
Successful	70	2	68	97
Total	140			95

Financial failure prediction two years prior to failure with the CART method. In order to predict financially failed businesses two years in advance, the financial ratios calculated for businesses in the sample were used as independent variables in the CART analysis.

In the first stage of the CART analysis, the 29 independent variables consisting of financial ratios of 140 businesses were analyzed and a maximal tree indicating an elaborate correlation between variables was constructed. After the construction of the maximal tree, a new tree was constructed by gradually pruning it from bottom to top, beginning from the very bottom child node ensuring that the tree constructed had fewer nodes and a higher incorrect classification rate than the previous tree. The optimal tree, which assures the best balance between the decreases in the number of nodes with the increase in rates of incorrect classifications after the process of pruning using the tenfold cross validation test, is presented in Figure 3.

According to the constructed optimal tree, the income/total liabilities + equity was determined to be the most important variable with the best split with income/total liabilities + equity ≤ -0.000420 indicating the business is failed and income/total liabilities + equity > -0.000420 indicating the business is successful. In light of this criterion, the accuracy of the CART method in predicting the financial situation two years in advance is shown in Table 2.

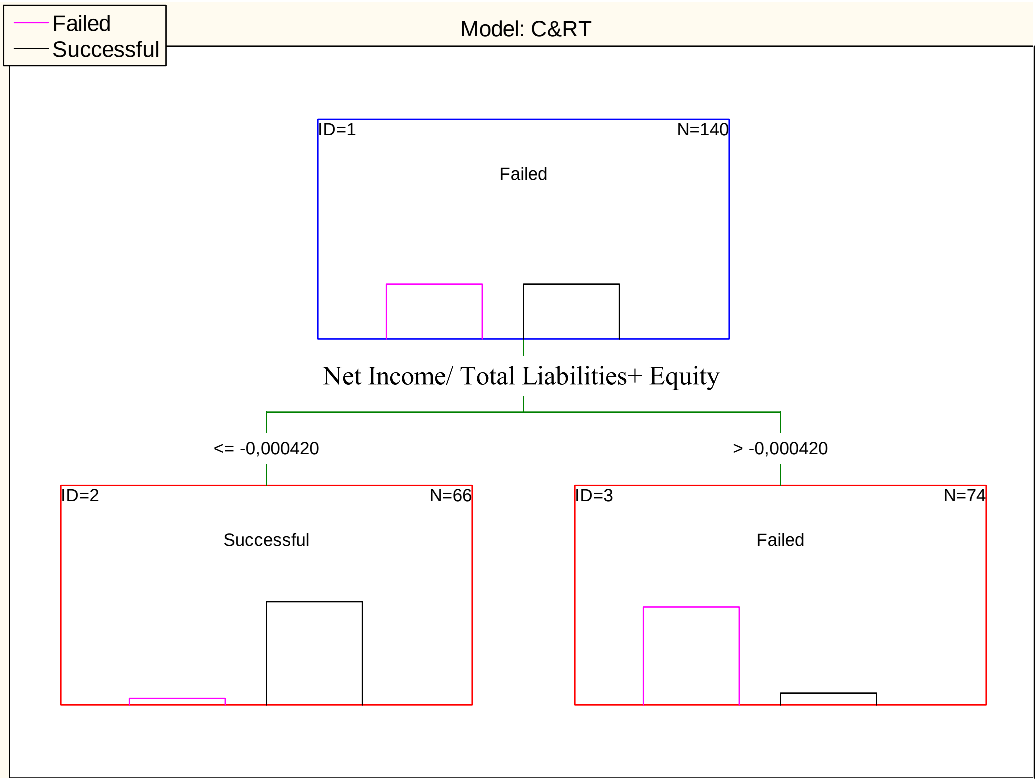

Figure 3. Optimal tree constructed in an attempt to predict financial failure two years in advance.

Table 2

The Accuracy of CART Method in Prediction Two Year Prior to Failure

Total sample	Number	Predicted group membership		Accuracy in prediction (%)
		Failed	Successful	
Failed	70	66	4	94.3
Successful	70	8	62	88.6
Total	140			91.4

As can be seen in Table 2, the CART method accurately predicted financial failure of 66 out of 70 unsuccessful businesses two years prior with an accuracy of 94.3%, and 62 out of 70 successful businesses were predicted accurately at a rate of 88.6%. The classification rate of both successful and failed businesses two year prior is 91.4% by the model.

Financial failure prediction three years prior to failure with the method. The analysis was conducted using financial ratios of both successful and unsuccessful businesses three years prior to the year in which they had been determined successful or failed. In the first stage of the classification and regression analysis, independent variables were included in the analysis and the maximal tree was constructed. Subsequently, a new tree was constructed by gradually pruning it from bottom to top, beginning from the very bottom child nodes ensuring that the tree constructed had fewer nodes and a higher incorrect classification rate than the previous. Among all the trees obtained, the optimal tree, which assures the best balance between the decreases in the number of nodes with the increase in rates of incorrect classifications after the process of pruning using the 10 fold cross validation test, is presented in Figure 4.

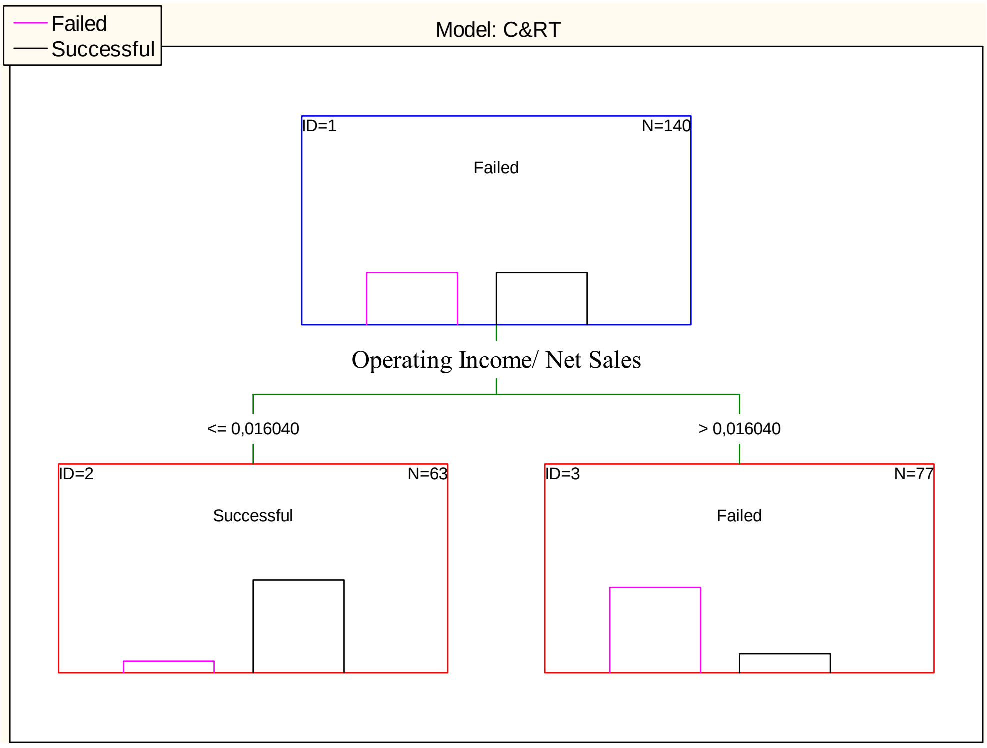

Figure 4. Optimal tree constructed in an attempt to predict financial failure three years in advance.

According to the optimal tree constructed, due to developing the best split the Operating Income/Net Sales was the most important, with Operating Income/Net Sales ≤ 0.016040 indicating the business was unsuccessful and Operating Income/Net Sales > 0.016040 indicating the business was successful. The accuracy of the CART method in predicting the financial failure three years prior to failure is shown in Table 3.

Table 3
The Accuracy of CART Method in Prediction Three Year Prior to Failure

Total sample	Number	Predicted group membership		Accuracy in prediction (%)
		Failed	Successful	
Failed	70	63	7	90
Successful	70	14	56	80
Total	140			85

As shown in Table 3, the model accurately predicted 63 out of 70 failed businesses with an accuracy of 90%, and 56 out of 70 successful businesses were predicted accurately at a rate of 85%, three years prior to failure time. In more general terms, the rate of the model's accuracy in classifying both successful and unsuccessful businesses was 85%.

Conclusions

Financial failure in businesses affects groups including stockholders, owners, managers, bondholders, creditors, and employees who are directly related to that businesses as well as the overall economy of the country and therefore the significance of developing early warning models that let us predict the financial failure have been accentuated. Single and multivariate statistical models have been used in financial failure prediction. Even though various methods used in financial failure prediction exist, as it is not possible to obtain one that would provide the best results in every circumstance and business environment resulted in a search for a new model. One of the new methods is the CART method.

The CART method fundamentally aims at developing a model which predicts the value of dependent variables by using independent variables in a nonparametric way.

In this study, the CART model which has seen greater use in recent times is explained, and its accuracy in prediction failure was tested on businesses whose stocks were listed on the ISE. The criteria that are used to determine failure were bankruptcy, negative equity, losses for three years in a row, listed in the watch list companies market for financial difficulties and being delisted. In light of these criteria, 70 financially failed businesses were identified and matched with the same number of successful businesses. In the analyses, 29 ratios of liquidity, financial structure, turnover and probability are applied as independent variables.

With such an analysis, the CART model accurately predicted the failure of 65 out of 70 unsuccessful businesses (92%) one year prior to failure, and 68 out of 70 successful businesses (97%). The predictive accuracy of successful and unsuccessful businesses is 95%. The probability ratios constitute the most effective measure when compared to other ratios in determining successful and failed businesses one year in advance.

The predictive accuracy for failed businesses is found to be 94.3%, successful businesses 88.6% and overall 91.4% according to analysis conducted for a period two years prior to financial failure. It is stated that the probability ratios were once again the most effective in determining successful and failed businesses during this term.

As a result of the analysis conducted in order to predict financial failure with the CART method 3 years prior to failure, 63 out of 70 unsuccessful and 56 out of 70 successful businesses are predicted accurately. The accuracy rate of the model is 90% for unsuccessful businesses, 85% for successful businesses, and 85% overall, and appears to be that the probability ratios were also more effective, when compared to other ratios, in differentiating successful and unsuccessful businesses during this term.

The CART method managed to accurately predict successful and failed businesses one, two and three years prior to failure with a high level of accuracy. Prediction power decreases linearly as the number of years prior to failure increase. The probability ratios are the most effective measure in identifying successful and failed companies.

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Appendix Financial ratios used in financial failure prediction models

Liquidity ratios	
X_1	Current ratio (Current asset/Current liabilities)
X_2	Acid-Test ratio (Current asset-Inventories)/Current liabilities
X_3	Cash ratio (Liquid assets + Marketable securities)/Current liabilities
X_4	Inventories to total assets
X_5	Total short term receivables/Total assets
X_6	Current liabilities/Equity
Financial structure ratios	
X_7	Current liabilities + Long term liabilities/Total liabilities.
X_8	Current liabilities/Total liabilities
X_9	Long term liabilities/Total liabilities.
X_{10}	Long term liabilities/(Long term liabilities + Equity)
X_{11}	Fixed assets/Equity
X_{12}	Current assets/Total liabilities + Equity
X_{13}	(Current liabilities + Long term liabilities/Equity
Turnover ratios	
X_{14}	Net sales/(Cash + Marketable securities)
X_{15}	Net sales/Tangible assets
X_{16}	Net sales/(Short term receivables + Long term receivables)
X_{17}	Net sales/Fixed assets
X_{18}	Net sales/Equity
X_{19}	Net sales/Current assets
X_{20}	Net sales/Total assets
X_{21}	Cost of good sold/Inventories
Profitability ratios	
X_{22}	Net Income/Equity
X_{23}	EBIT/Total liabilities + Equity
X_{24}	Net Income/Total liabilities + Equity
X_{25}	Operating income/Net sales
X_{26}	Net income/Net sales
X_{27}	Gross profit or loss/Net sales
X_{28}	Earnings before tax/Net sales
X_{29}	EBIT/Interest expenses