Corporate Credit Risk Assessment of BIST Companies

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Abstract

Assessing credit risk allows financial institutions to plan future loans freely, to achieve targeted risk management and gain maximum profitability. In this study, the constructed risk assessment models are on a sample data which consists of financial ratios of enterprises listed in the Bourse Istanbul (BIST). 356 enterprises are classified into three levels as the investment, speculative and below investment groups by ten parameters. The applied methods are discriminant analysis, k nearest neighbor (k-NN), support vector machines (SVM), decision trees (DT) and a new hybrid model, namely Artificial Neural Networks with Adaptive Neuro-Fuzzy Inference Systems (ANFIS). This study will provide a comparison of models to build better mechanisms for preventing risk to minimize the loss arising from defaults. The results indicated that the decision tree models achieve a superior accuracy for the prediction of failure. The model we proposed as an innovation has an adequate performance among the applied models

Keywords: ANFIS, Neuro-fuzzy systems, credit risk, risk assessment

Introduction

The main purpose of the Credit Risk assessment (CRA) is to speed up the investor's decision-making process by making it easier for the investor to compare the investment risks (Adalı, 2011). Even small improvements in credit risk assessment would provide a great benefit for the financial institutions. In this regard, continuous proposals were presented to improve the accuracy of risk assessment.

The rating process is based on the qualitative and quantitative data. However, only the quantitative data expresses a numerical value, which is why most of the studies on credit risk assessment are performed with the quantitative data. Many previous studies on the credit risk employed financial ratios as risk indicators (see Agha & Faff, 2014; Altman et al., 1977; Arundina et al., 2015; Blume et al., 1998; Chen & Cheng, 2013; Hajek & Michalak, 2013; Hensher et al., 2007; Jones and Hensher, 2004; Jorion et al., 2009; Manzoni, 2004; Shumway, 2001). The quantitative studies aimed to classify the good and bad credit applicants or assign the level of applicants as the investment, speculative or below investment.

While expert systems are extensively used by the organizations, studies on neuro-fuzzy systems captured the attention as the traditional models no longer answer the needs for efficient credit risk assessment. The models built in this study are SVM, DT, DA, k-NN and the new proposed model ANN+ANFIS. Among these mentioned models, decision tree algorithms are considered as the most accurate model of our study, which is followed by the proposed new model, namely ANN+ANFIS.

Methodology

This study, which aims to classify enterprises by their risk levels, is performed on 356 enterprises from BIST. The study is carried out in two stages. In the first stage, the enterprises that do not have a score are rated as the investment, speculative and non-investment risk levels with respect to their debt ratio specification. In the second stage, five different methods were implemented on the obtained dataset.

Dataset Collection

The dataset is formed by the ratios retrieved from the financial statement of enterprises functioning in BIST (Istanbul Stock Exchange). Financial information of the BIST traded companies are derived from the Public Disclosure Platform. The obtained variables are debt ratio, current ratio, EBITM, equity ratio, sales, ROE, TFAE, long-term debt over total debt and long-term debt over equity.

The aim of the applied methodology is to find the significant variables that made the maximum contribution to the explanation of the dependent variable by using the financial information provided on the balance sheets. Mitrut & Simionescu (2014) asserted a method with linear regression analysis involving different dependent variables and concluded that the variable with higher R^2 was more accurate in the predictions.

Sawyer and Stokes (2003) contrast the R-squared values of variables and display the proportion of variability in the dependent variable that was accounted for by the independent variable. Frank (2009) prefer the usage of R-Squared method as a measure of relevance, with variables whose relevance depended on the measure of the R-Square. In other words, variables that had the highest R-Square were the most relevant, while those with the lowest were the least relevant.

In this study, we selected the debt ratio as the ratio which is sufficient to rate a company's credit worthiness. The debt ratio represents the dependent variable and the other ratios taken as the independent variable group. The debt ratio has a $R^2 = 0.859$, which means that 85.9% of the total variation can be explained by the independent variables. Once the dataset was obtained, the methodology of the research was determined as a comparative study for the CRA. We reduced the dataset and had a logarithmic transformation to obtain normality. "Dimensionality reduction techniques can be applied to the input data to obtain a reduced representation of the dataset without losing the integrity of the original data" as claimed by Han and Kamber (2001),

A multiple linear regression is employed for the feature selection and the maximum accuracy is obtained with ten selected variables. Figure 2.1 illustrates the concept model of the study.

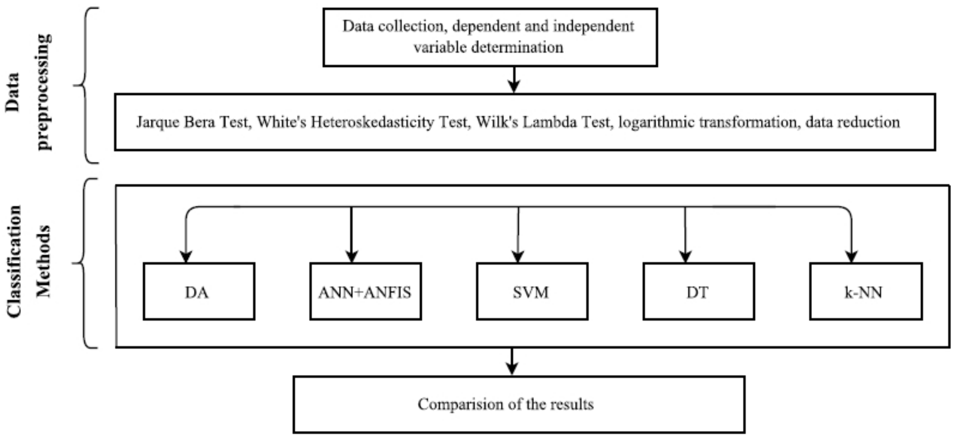

FIGURE 2.1 Concept Model of the Research

Applied Models

- Modeling techniques can be categorized into two main titles, namely as statistical methods and newly developed techniques such as machine learning algorithms.

Statistical Methods Used to Assess Credit Risk

- Eisenbeis (1978) reviewed the credit scoring models and attracted attention to the methods that were employed as well as the statistical problems concerned with models using discriminant analysis. Steenackers & Goovaerts (1989) utilized the logistic regression model to develop a scoring system for personal loans. Their technique performed many logistic regressions for the variable with the most predictive ability to achieve the desired significance level. Logistic regression models are a special form of the general linear models obtained for a binomial distribution dependent variable. Logit analysis has been employed since 1981 to avoid the presumptive limitations of the discriminant analysis (Karaa,2015).

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The Quantitative Analysis of financial distress generally involves two statistical methods regression and discriminant analysis (Glantz, 2003). Discriminant analysis was the first method used to develop credit-scoring systems by Durand (1941), who brought the methodology to finance for distinguishing between good and bad consumer loans. Beaver (1966) had a comprehensive study on financial ratios as predictors of failure. Altman (1968) introduced the prediction of corporate bankruptcy. A set of financial ratios were investigated in a bankruptcy prediction context and a multiple discriminant statistical model was employed on the data of manufacturing corporations. The purpose of the discriminant analysis is to find the best combination of ratios, which classifies the groups (Deakin, 1972). DA involves the determination of a linear equation like regression that predicts which group the case belongs to (Sinyangwe & Muller, 2014). The form of the equation or function is:

$$D = v_1 X_1 + v_2 X_2 + v_3 X_3 + ... + v_i X_i + a \qquad (2.1)$$

Where D= discriminant function

v= the discriminant coefficient or weight for that variable

X= respondent’s score for that variable

a= a constant

Machine Learning Techniques Used to Assess Credit Risk

Desai, Crook, and Overstreet (1996) explored the neural networks like MLP and modular neural networks as well as the traditional techniques such as DA and logistic regression for credit scoring. They observed that logistic regression models are as efficient as the neural networks approach. The performance of traditional models is not superior to NN and logistic regression. Chen & Huang (2003) worked on two interesting credit analysis problems applying neural networks (NNs) and GA in solution. Applicants were classified into two groups as accepted or rejected by the neural network credit-scoring model.

Hybrid approaches are new machine learning paradigms, which is advantageous in many applications. Wang and Ma (2012) proposed RSB-SVM model as a new hybrid system, which is based on two ensemble strategies, Random Subspace and SVM. Hsieh (2005) presented a hybrid mining approach by clustering and neural network techniques. The clustering stage involved a class-wise classification process. Samples with new class labels were used in the design of the credit-scoring model. Wang, Hao, Ma & Jiang (2011) conducted a comparative assessment by Logistic Regression

Analysis (LRA), Decision Tree (DT), Artificial Neural Network (ANN) and Support Vector Machine (SVM).

ANFIS is adaptive networks that are built to support the functionality of fuzzy inference systems. Malhotra & Malhotra (2002) made a comparison of artificial neuro-fuzzy inference systems (ANFIS) and multiple discriminant analysis models. Findings of their study showed that the neuro-fuzzy system performs better than the multiple discriminant analysis and that ANFIS has many advantages over traditional methods.

Results

The dataset has 356 samples with 10 features classified in investment, speculative and non-investment risk levels. Distribution of levels is not homogeneous as 176 companies are in the investment, 47 are in speculative and 135 of them are at the non-investment level.

Table 3.1 shows that out of 173 investment level firms 4 are misclassified. There exist 47 speculative level firms 36 of which are misclassified. Furthermore, from 135 non-investment level firms, 12 of them are not classified accurately by the DA**.** As a general result, 85.4% of original grouped cases are correctly classified.

ANN+ANFIS is an adaptive network that is built to speed up the training phase of the ANFIS structure. The problem with ANFIS is its inability to process many features (inputs) because of exponentially growing IF-THEN rule numbers. ANN is used to provide a trained and reduced number of inputs.

TABLE 3.1 Discriminant Analysis Results

Classification Results						
RATING			Predicted Group Membership			Total
			1	2	3	
Original	Count	1	169	4	0	173
		2	34	11	2	47
		3	8	4	123	135
	%	1	97.7	2.3	0	100
		2	72.3	23.4	4.3	100
		3	5.9	3	91.1	100

The fuzzy rules are in the form of if-then statements which are formed by expert knowledge. If all the attributes are used in every rule and a rule is formed for each possible combination of all attributes, then there are exponentially growing number of rules which can be represented by:

$$\prod_{i=1}^{n} N_i = N_1 \cdot N_2 \cdot \ldots\ldots \cdot N_n \qquad (3.1)$$

The structure of the built network is given in Table 3.2.

TABLE 3.2 ANN+ANFIS Network Structure

Parameter	Setting
Hidden layer neurons	10,40,1
Input neurons	9
Learning Algorithm	trainlm
Transfer functions	logsig, tansig, purelin
Membership function	gbellmf

The network has an input layer with nine neurons, three hidden layers 10-40-1 neurons and an output layer with one neuron. There are nine neurons in the input layer for each predictor variable. “trainlm“ is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. It is often the fastest backpropagation algorithm in the toolbox ("Levenberg-Marquardt backpropagation - MATLAB trainlm - MathWorks United Kingdom", 2018). Figure 3.1 shows the MSE of the best training performance of the system.

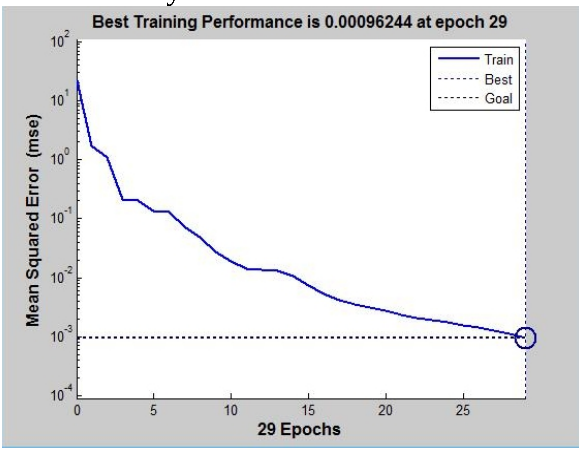

FIGURE 3.1 Best Training Performance of ANN

Experiments point out that SVM is a powerful classification method since it has outperformed most of the other methods in a wide variety of applications, such as text categorization and face or fingerprint identification (Yu, 2008). Wang and Lai (2005) proposed a fuzzy support vector machine to discriminate the customers and found out that the new fuzzy support vector machine has more classification ability.

The k-NN algorithm was also employed because of ease of use for approximating continuous-valued target functions. In order to do this, we have the algorithm to calculate the mean value of the k nearest training examples rather than calculate their most common value (Mitchell, 1997). If m_j represent the number of units that belong to Group j. The probability of unit u belonging to Group j is estimated by:

$$\hat{P}(j|x_u) = \frac{q_j \cdot m_j}{\sum_{j'}^{j} q_{j'} \cdot m_{j'}} \tag{3.2}$$

Decision tree algorithms appear as one of the most accurate methods for classification. Another reason that makes us choose decision trees as the principal modeling approach is their simplicity. The Random Forest model has the highest accuracy of classification with 99.44%. Figure 3.2 is the WEKA output of REP tree model, which has 99.16% accuracy of classification.

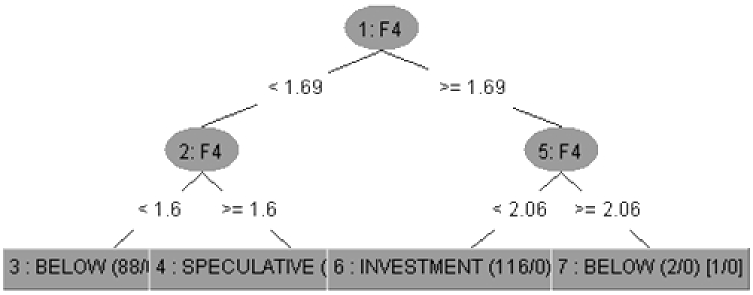

FIGURE 3.2 REP Tree Model

The comparison of proposed CRA Model accuracy with other models is given in Table 3.3. Decision tree algorithms are the most accurate model of our study, which is followed by the proposed new model ANN+ANFIS.

TABLE 3.3 Comparison of Analysis Results

	REP Tree	Random Tree	Random Forest	SVM	k-NN
Correctly Classified Instances	353	345	354	300	273
Incorrectly Classified Instances	3	11	2	56	83
Kappa statistic	0.9859	0.9486	0.9906	0.717	0.6177
Mean absolute error	0.0111	0.0206	0.0324	0.2865	0.1581
Root mean squared error	0.0747	0.1435	0.0778	0.372	0.3924
Relative absolute error	0.0277	0.0515	0.0809	0.7156	0.3949
Root relative squared error	0.1669	0.3209	0.1739	0.8318	0.8775
Total Number of Instances	356	356	356	356	356

In the learning process of the proposed hybrid model, many parameters affected the accuracy of the system. Enhancement of the structure of network or augmentation of the number of samples could give a better performance. Also by the usage of a different order of transfer functions and a different membership function, we could obtain higher accuracy in ANFIS. There are many different training algorithms, with different characteristics and performance. A set of models could be developed by the employment of training algorithms other than trainlm. The reason why the hybrid system didn't surpass the decision tree algorithms is the need for the adjustment of the system components and to build new hybrid structures.

As shown in Table 3.4 the Random Forest model had the highest accuracy of classification with 99.44% of the instances. The model we proposed has a satisfying performance with 90.46 %. As a statistical method discriminant analysis could not outperform the proposed model.

Table 3.4 Percentages of accuracy for the employed models

Model	Accuracy %
Discriminant	85.4
SVM	84.27
k-NN	76.69
ANN+ANFIS	90.46
Random Forest	99.44
Random tree	96.91
REP Tree	99.16

A question arises whether there is a significant difference among the risk levels of firms according to their sectors. To answer this question, we have performed analysis of variance. The results given in Appendix 1 indicate that the highest risk level belongs to the sector 20 (Transportation, Storage & Communication Sector) and sector 18 (Service Sector) which is followed by the sector 14 (Energy Sector). Appendix 2 gives the mean of the risk level of companies in different scales. The highest risk level belongs to the scale 4, which represents large-scale companies, and the lowest risk level belongs to the scale 1, which denotes micro-scale companies.

Conclusion

The necessity of a quick evaluation and transfer of information increases the importance of credit assessment and rating process. Models are being improved by the increasing number of studies and the approaches offer an alternative to other classification techniques. Through an accurate assessment of credit risk, it is possible for domestic enterprises to protect their credibility. CRA activities promote the strength of financial structures and the restriction of risks. They are also helpful in providing a coherent framework for the risk management strategy to inform potential future investors. Besides these, CRA activities improve relations with international finance environments. From this aspect, the study has contributions to enterprises and investors as well as the financial institutions. The use of public information also illustrates that this is a relatively cost-effective alternative to assess credit risk.

As the main innovation, our proposal explores the combination of ANN and ANFIS models to optimize a model's structure. We evaluate our approach in comparison to individual classifiers. Empirical results indicate that the proposed model is a solution for credit risk problems, being able to compete in accuracy with decision trees in producing structures for CRA decisions. For the further study, larger datasets could be collected for longer time intervals and the risk level of each firm could be assessed in its sector to analyze the trend of events in various sectors.

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APPENDICES

Appendix 1 Percentage of Firms in Investment Level for Each Sector

Sector	Investment	Speculative	Non-Investment	Risk level Mean	Percent of firms in investment level
1	15	5	13	1.939	45.45
2	12	5	11	1.964	42.86
3	12	7	10	1.931	41.38
4	8	3	9	2.05	40
5	15			1	100
6	8	2	5	1.8	53.33
7	2		4	2.333	33.33
8	5			1	100
9	1		2	2.333	33.33
10	6	1	1	1.375	75
11	8	2	8	2	44.44
12	2	1	2	2	40
13	3			1	100
14	2	1	8	2.545	18.18
15	1	1	4	2.5	16.67
16	7	4	1	1.5	58.33
17	24		2	1.154	92.31
18	1	2	5	2.5	12.5
19	1		3	2.5	25
20	1		7	2.75	12.5
21	20	6	15	1.878	48.78
22	8	1	8	2	47.06
23	12	6	17	2.143	34.29

Appendix 2 Percentage of Firms in Investment Level for Each Scale

Scale	Investment	Speculative	Non-Investment	Risk level Mean	Percent of firms in investment level
1	32	8	15	1.691	58.18182
2	39	7	20	1.712	59.09091
3	43	13	23	1.747	54.43038
4	60	19	77	2.109	38.03738