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Predicting bank financial failures using neural networks, support vector machines and multivariate statistical methods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey

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Abstract

Bank failures threaten the economic system as a whole. Therefore, predicting bank financial failures is crucial to prevent and/or lessen the incoming negative effects on the economic system. This is originally a classification problem to categorize banks as healthy or non-healthy ones. This study aims to apply various neural network techniques, support vector machines and multivariate statistical methods to the bank failure prediction problem in a Turkish case, and to present a comprehensive computational comparison of the classification performances of the techniques tested. Twenty financial ratios with six feature groups including capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk (CAMELS) are selected as predictor variables in the study. Four different data sets with different characteristics are developed using official financial data to improve the prediction performance. Each data set is also divided into training and validation sets. In the category of neural networks, four different architectures namely multi-layer perceptron, competitive learning, self-organizing map and learning vector quantization are employed. The multivariate statistical methods; multivariate discriminant analysis, *k*-means cluster analysis and logistic regression analysis are tested. Experimental results are evaluated with respect to the correct accuracy performance of techniques. Results show that multi-layer perceptron and learning vector quantization can be considered as the most successful models in predicting the financial failure of banks.

Keywords: Bankruptcy prediction; Financial failure; Banking; Savings deposit insurance fund; Artificial neural networks; Support vector machines; Multivariate statistical analysis

1. Introduction

The Turkish banking sector was severely tested in the aftermath of the 1994 financial crisis. The banks that carried a significant short position in foreign exchange position, mismatch of maturities had to incur large losses and faced liquidity problems as a result of a major run on deposits. Three small banks were put on liquidation process in April 1994, which triggered further deposit withdrawals. The government had to introduce a 100% guarantee to savings deposits and provide liquidity support to the banks that were facing difficulty. However, except for three small banks that were liquidated, the banking sector proved to be resilient and a banking crisis was avoided. These developments highlight the fact that the Turkish banking sector is highly segmented, with a group of efficient and profitable banks at the core and other smaller banks at the margin. The banking sector recovered rapidly from the 1994 financial crisis. However, the East Asia and Russian crises of 1997–1998 together with the two devastating earthquakes of 1999 had a negative impact on the

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Turkish economy and the banking sector. A November 2000 crisis led to a significant erosion of the capital base of the banking sector and revealed further the fragility of the system. The escalating political uncertainties, the loss of credibility of the exchange rate regime and finally the abolition of the exchange rate peg in February 2001 further hit the already weak banking sector (BRSA, 2001). During the November 2000 and February 2001 crises, some banks failed financially. Consequently, some banks ceased their operations and some banks were taken over by the Savings Deposit Insurance Fund (SDIF) (Doganay, Ceylan, & Aktas, 2006).

SDIF is charged with strengthening and restructuring the financial structure of the banks when necessary besides insuring savings deposits. The administration and representation of the SDIF having legal entity as of 1983 were first enforced by the Central Bank of Republic of Turkey (CBRT) and then the Banking Regulation & Supervision Agency (BRSA).[1] It was provisioned in 2003 that the decision-making body of the SDIF is the Fund Board. (http://www.tmsf.org.tr).

The legal basis regarding the take-over of banks by the SDIF is as follows: Upon decision of the Banking Regulation and Supervision Board (BRSB), license of the bank to perform banking activities and to accept deposits are revoked pursuant to Article 71 of the Banking Law No. 5411. While the bank in question can not timely fulfill its obligations, it does not take the required measures, and the continuation of its banking activities will jeopardize depositors' rights as well as the safety and soundness of the financial system. Therefore, the control and management hereof is taken-over by the SDIF pursuant to Article 106 of the same law. The SDIF shall pay the insured deposits and insured contribution funds with the bank whose management and control has been assumed by it; directly or through another bank, it may designate and institute bankruptcy proceedings in the name of the owners of deposits and contribution funds against the bank. The SDIF shall be exclusively authorized to take the foregoing actions pursuant to Article 106 of the same law (BRSA, 2003).

Since 1997, 21 banks were transferred to the SDIF. These banks have been promptly resolved through direct liquidation by repayment of all liabilities, liquidation by repayment of liabilities subject to deposit insurance system, merged and finally, sold off after a financial and/or operational restructuring process. At present, only one bank, Birlesik Fon Bankasi, remains under the auspices of the SDIF. Table A.1 of Appendix presents the detailed information on the liquidation process of banks taking-over by the Fund (SDIF, 2006).

[1] BRSA is a public legal entity having financial and administrative autonomy in Turkey. As the independent authority it regulates and supervises the banking sector. It was established to safeguard the rights of depositors, to ensure banks to operate in a healthy and efficient manner, and to ensure efficient functioning of the credit system. BRSA has started to operate in August 2000.

Bank failures in the period from 1997 to 2003 deeply affected the real sector and the households, because of the central position of the banks in the economy (Doganay et al., 2006). Predicting the possible bank failures in such a risky banking sector is crucial to prevent and/or lessen its effects on the whole economic system. On the other hand, the importance of this prediction problem makes comparative analyses for different approaches also important. Predicting bank failures is originally a classification problem to categorize banks as healthy or non-healthy ones. This problem has been extensively studied by many researchers and a number of methodologies have been developed. The literature on bankruptcy prediction generally includes multivariate statistical methods and artificial neural networks (ANN). Recently, support vector machines (SVMs) have become a focus of interest for bankruptcy prediction. However, especially in the Turkish case, the literature on comparing different approaches for this problem is relatively narrow. The main goal of this study is to apply various neural network techniques, support vector machines and multivariate statistical methods to bank failure prediction problem in the Turkish case, and to present a comprehensive computational comparison of the classification performances of these techniques.

The rest of the paper is organized as follows: A comprehensive literature review on financial failure prediction is given in Section 2. Section 3 provides the research design and methodologies in terms of data, variables, and classification techniques used for the study. Results of the experiments are given and discussed in Section 4. Some general conclusions are drawn in the last section.

2. Literature review

The prediction of failure for financial firms, especially banks, has been an extensively researched area since late 1960s. A variety of statistical methods and neural network topologies have been applied to solve bankruptcy prediction problem in banks and firms. Statistical methods include linear discriminant analysis (LDA), multivariate discriminate analysis (MDA), quadratic discriminant analysis (QDA), multiple regression, logistic regression (logit), probit and factor analysis (FA). The neural networks topologies covered in the literature belong to different neural network architectures including multi-layer perception (MLP), radial basis function network (RBFN), probabilistic neural network (PNN), auto-associative neural network (AANN), self-organizing map (SOM), learning vector quantization (LVQ), cascade-correlation neural network (Cascor) and other intelligent techniques including support vector machines, fuzzy logic and isotonic separation (Kumar & Ravi, 2007).

Altman (1968) is the first researcher who used discriminant analysis to predict the failures of firms from different industries. Sinkey (1975) also employed discriminant analysis to predict bank failures. Altman (1977) in a later study developed a discriminant model to predict the failures of the Savings and Loan Associations for the period of 1966–1973 using 32 ratios as explanatory variables. Lam and Moy (2002) combined several discriminant models, and performed simulation analysis to enhance the accuracy of classification results for classification problems in discriminant analysis.

Another multivariate statistical method that is used to predict bank failures is multiple regression analysis. Meyer and Pifer (1970) are the first researchers who used this method to predict bank failures.

Martin (1977) and Ohlson (1980) employed logistic regression to predict banks and firms failure. Thomson (1991) examined the bank failures that took place in the United States during the 1980s. Gonzalez-Hermosillo (1999) investigated bank failures in the United States, Mexico and Colombia occurred in the 1980s and 1990s. Kolari, Glennon, Shin, and Caputo (2002) developed an early warning system based on logit analysis and Trait recognition for large US banks. Jones and Hensher (2004) presented mixed logit model for firm distress prediction and compared it with multinomial logit models. Montgomery, Hanh, Santoso, and Besar (2005) investigated bank failures in Japan and Indonesia using logit. Canbas, Cabuk, and Kilic (2005) proposed an integrated early warning system by combining discriminant analysis, logistic regression, probit and principal component analysis. Konstandina (2006) used logit analysis to predict Russian bank failures. Doganay et al. (2006) developed an early warning system by combining multiple regression, discriminant analysis, logit and probit.

Neural networks (NNs) found extensive applications in bankruptcy prediction. Odom and Sharda (1990) were the first to apply NNs for the prediction of company failure. Tam (1991) employed back propagation neural network (BPNN) for bankruptcy prediction. Tam and Kiang (1992) compared the performance of LDA, logistic regression, K-NN, ID3, feed-forward NN and BPNN in bankruptcy prediction problems. Salchenberger, Mine, and Lash (1992) and Fletcher and Goss (1993) used the BPNN for predicting bankruptcy of savings, loan associations and firms and compared its performance with logistic regression. Sharda and Wilson (1993) compared the BPNN with MDA based on the re-sampling technique. Altman, Marco, and Varetto (1994) compared the performance of LDA with BPNN in distress classification. Wilson and Sharda (1994) compared the predictive accuracy of BPNN with that of DA. Tsukuda and Baba (1994) performed the prediction of bankruptcy using BPNN with one hidden layer and concluded that BPNN outperformed the DA. Leshno and Spector (1996) compared various NN models and DA. Jo and Han (1996), suggested an integrated model approach for bankruptcy prediction; the discriminant analysis and two artificial intelligence models, neural network and case-based forecasting, and conclude that the integrated models produced higher prediction accuracy than individual models. Lee, Han, and Kwon (1996) proposed three hybrid BPNN namely MDA-assisted BPNN, ID3-assisted BPNN and SOM-assisted BPNN for predicting bankruptcy in firms. They concluded that hybrid neural network models performed better than MDA and ID3. Serrano-Cinca (1996) compared the performance of SOM with LDA and BPNN in financial diagnosis. Jo, Han, and Lee (1997) applied the three forecasting techniques of DA, case-based forecasting, and neural network for predicting the bankruptcy of Korean firms. They concluded that NN outperformed DA and case-based forecasting system. Barniv, Anurag, and Leach (1997) compared BPNN, multi-state ordered logit and non-parametric multiple discriminant analysis (NPDA). They concluded that BPNN outperformed NPDA and logit models. Bell (1997) compared logistic regression and BPNN in predicting bank failures. Piramuthu, Ragavan, and Shaw (1998) designed a method called feature construction (FC) and used it with BPNN for bankruptcy prediction. They concluded that BPNN with FC outperformed the plain BPNN in all data sets. Kiviluoto (1998) used SOM and proposed its variants for firm bankruptcy prediction. He compared three different SOM-based classifiers namely SOM-1, SOM-2 and RBF-SOM hybrid with LDA, learning vector quantization (LVQ) and K-NN. Zhang, Hu, Patuwo, and Indro (1999) used generalized reducing gradient (GRG2) trained three-layered NN for bankruptcy prediction. They concluded that GRG2 trained NN outperformed logistic regression. Alam, Booth, and Thordason (2000) stated that fuzzy clustering algorithm and self-organizing neural networks approaches provide valuable information to identify potentially failing banks. Atiya (2001) developed novel indicators for the NN. He showed that the use of the indicators in addition to financial ratios provided significant improvement. Swicegood and Clark (2001) compared DA, BPNN and human judgment in predicting bank failures. They concluded that BPNN outperformed other two models in identifying under performance banks. Aktas, Doganay, and Yildiz (2003) used multiple regression analysis, logit, discriminant analysis and neural networks to construct financial failure prediction models for Turkish firms. They showed that neural networks outperformed all other techniques. Lee, Booth, and Alam (2005) compared BPNN with self-organizing feature map (SOM), DA and logistic regressions. They concluded that the BPNN outperformed the all other techniques.

Lacher, Coats, Sharma, and Fantc (1995) proposed a cascade-correlation neural network (Cascor) for classifying financial health of a firm. He compared the performance of the Cascor model with that of Altman Z-score model. They concluded that the Cascor model consistently yielded higher overall classification rates. Yang, Platt, and Platt (1999) proposed PNN without pattern normalization and Fisher discriminant analysis (FDA) to solve bankruptcy prediction problem. They compared the original PNN and PNN without pattern normalization (PNN*) and FDA with DA and BPNN. Baek and Cho (2003) proposed the auto-associative neural network (AANN) for Korean firm bankruptcy prediction. They concluded that AANN outperformed 2-class BPNN.

The literature dealing with the failure prediction problem using support vector machines (SVMs) is relatively small compared with statistical methods and neural networks. Shin, Lee, and Kim (2005) used SVMs for predicting the corporate bankruptcy and compared the results with BPNN. They showed that the accuracy and generalization performance of SVMs is better than that of BPNN as the training set size gets smaller. Min and Lee (2005) applied SVMs to the bankruptcy prediction problem in an attempt to suggest a new model with better explanatory power and stability. They compared the performance their model with DA, logit, and three-layer fully connected BPNN. Their experiment results showed that SVMs outperforms the other methods. Min, Lee, and Han (2006) proposed methods for improving SVMs performance in two aspects: feature subset selection and parameter optimization. They used genetic algorithms (GA) to optimize both a feature subset and parameters of SVM simultaneously for bankruptcy prediction. Recently, Wu, Tzeng, Goo, and Fang (2007) used a real-valued GA to optimize the parameters of SVMs for predicting bankruptcy and tested their model on the prediction of financial crisis in Taiwan to compare the accuracy of the proposed GA-SVMs model with that of other models in multivariate statistics (DA, logit, and probit) and artificial intelligence (NN and SVMs). They showed that the GA-SVM model performs the best predictive accuracy, implying that integrating the real-valued GA with traditional SVMs model is very successful. In general, the studies that used SVM to predict financial failure show that SVMs is better than neural networks and statistical methods in predicting the bankruptcy.

In addition to the statistical methods, neural networks and support vector machines, there are various intelligent techniques including case-based reasoning, decision trees, operational research, evolutionary approaches, rough set based techniques, soft computing techniques and other techniques subsuming fuzzy logic and isotonic separation developed for bankruptcy prediction in the literature. The review paper of Kumar and Ravi (2007) that summarizes the related literature can be useful for interested readers.

3. Research design and methodology

3.1. Data set development

A total of 20 financial ratios with six feature groups including capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk (CAMELS[2]) are selected as classifiers in the study. These financial ratios in six groups with their codes are as follows:

- *Capital adequacy*: Shareholder's equity/total assets (CA_1), shareholder's equity/total loans (CA_2), shareholder's equity + net profit/total assets + off balance sheet commitments (CA_3).
- *Asset quality*: Permanent assets/total assets (AQ_1), total loans/total assets (AQ_2), loans under follow-up/total loans (AQ_3), specific provision/total loans (AQ_4), specific provision/loans under follow-up (AQ_5).
- *Management*: Personnel expenses/average assets (M_1).
- *Earnings*: Net profit/average assets (E_1), net profit/average shareholder's equity (E_2), income before taxes/average assets (E_3), interest income/total operating income (E_4), non-interest expenses/total operating income (E_5).
- *Liquidity*: Liquid assets/total assets (L_1), total loans/total deposits (L_2).
- *Sensitivity to market risk*: Trading securities/total assets (SMR_1), FX assets/FX liabilities (SMR_2), net interest income/average assets (SMR_3), net on balance sheet position/total shareholder's equity (SMR_4).

A total of 21 banks were transferred to the SDIF in Turkey between 1997 and 2003. These are as follows: Turk Ticaret Bankasi (1997), Bank Ekspres (1998), Interbank, Esbank, Egebank, Yurtbank, Yasarbank, Sumerbank (1999), Bank Kapital, Etibank, Demirbank (2000), Iktisatbank, Sitebank, Kentbank, EGS Bank, Tarisbank, Bayindirbank, Toprakbank, Ulusalbank (2001), Pamukbank (2002) and Imarbank (2003). In addition to these failed banks, a total of 44 non-failed banks were also selected to include in the data set. Hence, the entire data set consisted of 65 banks. When selecting the non-failed banks, banks were randomly selected with the amount of double the number of failed banks for the corresponding year. Furthermore, two more non-failed banks were also randomly selected and included in the research data with their financial ratios for 2004. The research data used in the study is obtained from the annual publication "Banks in Turkey" issued by the Banks Association of Turkey (BAT). The above mentioned 20 financial ratios are calculated using these official data. To predict the bankruptcy status of a bank, the input data consisting of 20 financial ratios calculated for the bankruptcy year are used.

The entire data set is then divided into training and validation subsets. The training set consists of randomly chosen 14 banks which were transferred to the SDIF and 29 banks which were non-failed, whereas the validation set consists of 7 banks which were transferred to the SDIF and 15 banks which were healthy. Table 1 shows the summary of the research data used in the study.

The explained research data can now be applied to various prediction techniques with its pure form. Alternatively, to improve the classification performance, some variable reduction and normalization approaches can be applied to the financial ratios.

For each financial ratio, the difference between the means of failed and non-failed banks is compared with the independent samples t-tests. Following the t-tests the

[2] CAMELS is a supervisory rating system for evaluating bank's overall financial condition. It was first introduced in USA for on and off-site monitoring purposes. CAMELS has six components: Capital adequacy, Asset quality, Management quality, Earnings, Liquidity and Sensitivity to market risk (Kaya, 2001).

Table 1
The number of banks in the research data

Year	Entire set		Training set		Validation set	
	Failed	Non-failed	Failed	Non-failed	Failed	Non-failed
1997	1	2	0	1	1	1
1998	1	2	1	1	0	1
1999	6	12	4	8	2	4
2000	3	6	2	4	1	2
2001	8	16	5	11	3	5
2002	1	2	1	1	0	1
2003	1	2	1	2	0	0
2004	0	2	0	1	0	1
Total	21	44	14	29	7	15

ratios which do not show a significant difference are taken out of the pure data set and a new data set is created. The results of the t-tests for every single ratio are given in Table 2 below.

According to Table 2, amongst the 20 variables there is not a significant difference regarding 11 of them considering the banks which were transferred to the SDIF and which were non-failed. Therefore the rest 9 ratios are thought to be more useful in making a difference between the failed and non-failed banks. The reduced data set with 9 ratios may be more suitable to predict the bank failures and the experiments will be performed using this new data set separately.

In addition to the variable reduction, we can obtain two more data sets by normalizing the pure financial values. To achieve this, both the pure data set with 21 ratios and the reduced data set with 9 ratios are normalized to z-score. We have now four different data sets that can be used to classify failed and non-failed banks. All experiments of neural network models and SVMs are performed using each of these data sets separately and the best classification results are adopted.

Multivariate statistical methods such as discriminant analysis require uncorrelated variables. In order to determine whether there are correlations between the variables in the entire data set, Pearson Correlation coefficients were calculated. The correlation coefficients showed that significant multicollinearity among variables does exist. Factor Analysis can be applied to the 20 financial ratios in order to select combinations of ratios for use in the model. The object of factor analysis is to describe the covariance relationships among many variables in terms of a few underlying factors. However, the suitability of factor analysis to the financial data should be tested. To achieve this, Kaiser–Meier–Olkin (KMO) and Bartlett's Test of Sphericity were performed and the results are given in Table 3 below.

As it can be understood from both tests, where $p \leqslant \alpha$ at 5% significance level, H_0 hypothesis (H_o: $R = I$) is to be rejected whereas H_1 hypothesis (H_1:$R \neq I$) is to be accepted. As the correlation matrix (R) is not equal to identity matrix (I) there is a correlation between variables and KMO value with 53.7% is supporting this argument. According to these results, factor analysis can now be applied to the financial data.

As an extraction method the Principal Component Analysis (PCA) was applied to the data set. Banks are used as observation units whereas 20 financial ratios are employed as variables by PCA. During the first stage of the analysis, all financial ratios are standardized with a mean of 0 and the standard deviation of 1. The criterion chosen for deciding how many factors to retain are that the factors should account for at least 70% of the total variance and have a greater eigenvalue than 1. The eigenvalues of factors yielded by PCA are given in Table 4.

As shown in Table 4, seven factors were retained which explain 80.384% of the total variance. Then, for each factor, the ratio which is mostly related to this factor was selected for using in the multivariate statistical methods. To enhance the interpretability of financial factors, the varimax rotation method was employed and an increase in the conceptual meaningfulness of the factors was observed. Thus, the results of varimax method were used during interpretations.

The first factor which is taken into the model explains 21% of the total variance. This factor is the most important dimension in explaining changes of financial conditions of banks. The variables which are concentrated in the first factor, having the most explanatory power include active quality ratios (AQ_3, AQ_4). Active quality ratios are followed by capital adequacy ratio CA_2 and profitability ratio E1. Observed through conceptual meaningfulness this factor represents the active quality. The second factor explains 16% of total variance of the financial ratios and consists of capital adequacy ratios CA_1 and CA_3, liquidity ratio L_3 and management quality ratio M_1. This factor represents

Table 2
Results of the independent samples t-tests

Mean				Mean			
Ratio	Failed	Non-failed	t-statistic	Ratio	Failed	Non-failed	t-statistic
CA_1	1.59	10.18	2.54^{*}	E_2	−131.40	60.16	2.00^{*}
CA_2	−4.28	51.08	2.57^{*}	E_3	62.06	73.88	1.47^{ns}
CA_3	1.42	8.69	3.46^{***}	E_4	402.21	204.59	-0.57^{ns}
AQ_1	10.97	8.77	-1.14^{ns}	E_5	84.12	41.41	-0.36^{ns}
AQ_2	36.18	27.13	-2.66^{*}	L_1	45.73	56.11	1.99^{ns}
AQ_3	22.65	14.42	-0.70^{ns}	L_3	43.02	81.92	3.51^{***}
AQ_4	10.57	5.92	-0.70^{ns}	SMR_1	10.97	19.33	3.21^{**}
AQ_5	31.51	35.54	0.61^{ns}	SMR_2	2.08	19.21	2.44^{*}
M_1	3.37	3.30	-0.14^{ns}	SMR_3	12.78	13.27	0.15^{ns}
E_1	−6.55	5.28	3.20^{**}	SMR_4	−286.39	−166.23	1.66^{ns}

ns Not significant.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

Table 3
Results of KMO and Bartlett's test of sphericity

KMO		0.537
Bartlett's	Chi-Square	963.082
Test of	d.f.	190
Sphericity	Significance	0.000

Table 4
Eigenvalues of factors

Factors	Initial Eigenvalues			Factors	Initial Eigenvalues		
	Total	% of Variance	Cumulative (%)		Total	% of Variance	Cumulative (%)
1	4.261	21.303	21.303	11	0.457	2.286	93.079
2	3.204	16.022	37.325	12	0.346	1.728	94.807
3	2.825	14.124	51.449	13	0.294	1.470	96.276
4	2.100	10.501	61.949	14	0.223	1.116	97.393
5	1.393	6.967	68.916	15	0.180	0.900	98.293
6	1.239	6.194	75.110	16	0.135	0.673	98.966
7	1.055	5.274	80.384	17	0.110	0.551	99.517
8	0.805	4.023	84.406	18	4.165E−02	0.208	99.725
9	0.721	3.606	88.012	19	3.332E−02	0.167	99.892
10	0.556	2.781	90.793	20	2.163E−02	0.108	100.000

the capital adequacy. All the ratios grouped under this factor have also positive loadings. Any increase in the value of these ratios will lead to increase in the score of the capital adequacy factor. The third factor includes the ratios E_4 and E_5 which are related to profitability. This factor explains the percentage of 14.12 of total change. It represents the profitability factor. All the ratios grouped under this factor have also positive loadings. Increase in the value of these ratios will lead to increase in the score of the profitability factor. The fourth factor which explains 10.5% of total variance, includes active quality ratio AQ_2 and liquidity ratio L_1. In terms of conceptual meaningfulness this factor has the specifications of a mixed factor. The fifth factor includes the profitability ratio E4, active quality ratio AQ_5 and sensibility to market risk ratios SMR_1 and SMR_2. This factor explains 6.96% of total variance and represents sensibility to market risk. The sixth factor includes profitability ratio E_2 and sensibility to market risk ratio SMR_3. In terms of conceptual meaningfulness this factor has the specifications of mixed factor. The seventh factor includes only sensibility to market risk ratio SMR_4. The scores of these seven factors were used as independent variables in applying the multivariate statistical methods.

The output variable of the models is the status of banks failed or non-failed. The classification accuracy of classification techniques is the measure of prediction performance. This performance measure is the ratio of the number of correctly classified banks to the number of incorrectly classified banks. In this study, the classification accuracy is calculated for training and validation data sets separately. However, when evaluating the performance of any technique, its performance in validation data sets is considered as primary measures. The experiments using statistical methods are performed using SPSS while neural network and SVMs experiments are performed in MATLAB.

3.2. Artificial neural networks

Artificial neural networks (ANNs) is massively parallelized computing systems that have the ability to learn from examples and to adapt to new situations (Chu, 1997). A neural network normally consists of a set of neurons, a pattern of connectivity, a propagation rule, an activation rule, a transfer function and a learning rule (Rumelhart & McClelland, 1989). ANNs includes two working phases, the phase of learning and that of recall. During the learning phase, known data sets are commonly used as a training signal in input and output layers. The recall phase is performed by one pass using the weight obtained in the learning phase (Neaupane & Adhikari, 2006).

There are several neural network architectures to perform various categories of tasks. These architectures differ from each other with respect to the type of elements (Rumelhart & McClelland, 1989). In this paper, four different neural network architectures namely Multi-layer Perceptron (MLP), Competitive Learning (CL), Self-organizing Map (SOM) and Learning Vector Quantization (LVQ) are used to predict the bank failures.

An MLP is a feed-forward neural network with at least one hidden layer (Fu, 1994). MLP consists of fully connected feed-forward neural networks with an input, an output and one or more hidden layers in parallel. MLP is one of the most frequently used neural network model in the above four main categories of tasks. The MLP model belongs to the class of supervised neural networks. The supervised networks are adjusted or trained so that the network can approximate any non-linear function according to the given input–output pairs. MLP networks involve the minimization of an error function and they are trained by gradient descent method. The Back-propagation Algorithm (BPA) provides a way to calculate the gradient of the error function (Bose & Liang, 1996).

CL is one of the simplest paradigms of unsupervised learning (Chu, 1993). CL consists of competition and reward phases. A winner is selected in the competition phase and the winner is rewarded with an update of its weights in the reward phase (Bose & Liang, 1996). CL has been mostly used for classification of several input patterns. In the CL networks, input patterns are applied to the *input layer* and the units in the *competitive layer* compete to respond to the input pattern. Each unit in the competitive layer represents each class of input patterns. An input pattern is assigned to the winning unit in the competitive layer and the winning unit is rewarded by updating the weights connected to this unit. This process is repeated until the specified number of epochs is met.

A SOM which was introduced by Kohonen (1982) is a feed forward neural network consisting of input and output layers of neurons. In SOM, the map is typically constructed on a one or two-dimensional lattice of neurons (Hamalainen, Klapuri, Saarinen, & Kaski, 1997). The input layer is fully connected to this lattice. SOM forms clusters, without the need for extensive training, by accepting an input vector and classifying it into one of a number of categories depending on which of the several stored patterns it most resembles (Rao & Gu, 1994).

LVQ is an improved version of the original SOM. LVQ is such network architecture that is obtained by including the classification information in the input data and training the original SOM by supervised learning (Kohonen, 1995). The LVQ is simple three-layer network with the hidden layer neurons as a set of codebook vectors; a subset of these codebook vectors is assigned to each group (West, 2000).

The above networks were trained with different combinations of parameters such as the number of hidden layers, number of neurons for each layer, number of epochs and activation functions of neurons. The number of neurons in the input layer is equal to the number of variables in the data set. Since the output layer includes binary variables (0 or 1) the sigmoid activation function should be employed in the output layer. However different activation functions can be used in hidden layers.

The experiment consisted of the training of the networks with training data set and simulating the trained network with validation data set. The number of hidden layers and number of neurons in these layers were determined by starting with one empty hidden layer and adding neurons to this layer at a time. This process is maintained until the addition of new hidden layers and new neurons has no effect on the performance of the network.

3.3. Support vector machines

Support Vector Machines (SVMs) technique is a classification, recognition, regression and time series technique that is originated as an implementation of Vapnik's (1995) Structural Risk Minimization (SRM) principle. SVMs are based on mapping input space to a high-dimensional feature space where linear separation is easier than input space. SVMs use the pre-processing strategy in learning by mapping input space, X to a high-dimensional feature space, F (Seo, 2007). SVMs are used to find an optimal hyper-plane which maximizes the margin between itself and the nearest training examples in the new high-dimensional space and minimizes the expected generalization error. The training examples that are closest to the hyper-plane are called support vectors (Lee, 2007).

Although SVMs were originally developed for binary classifications, they have been applied to multi-classes problems. The failure prediction problem considered in the current study is a binary classification problem and SVMs can be applied to solve it. Data is modified from the input space into a high-dimensional feature space by using a kernel function. The kernel function decides the complexity of the classification function set, therefore affects the performance of an SVM (Yuan & Chu, 2007). Four kernel functions namely linear, polynomial, radial basis, and sigmoid are tested and the best one is adopted.

3.4. Multivariate statistical methods

In this group of prediction techniques, three multivariate statistical methods called Multivariate Discriminant Analysis (MDA), K-Means Cluster Analysis (CA) and Logistic Regression Analysis (LRA) are employed to predict the bank financial failures.

MDA is concerned with the classification of distinct sets of observations and it tries to find the combination of variables that predicts the group to which an observation belongs. The combination of predictor variables is called as a linear discriminant function, and this function can then be used to classify new observations whose group membership is unknown. The linear discriminant function is as follows:

$$D = B_{\mathrm{o}} + B_1X_1 + B_2X_2 + \ldots + B_{\mathrm{n}}X_{\mathrm{n}}, \tag{1}$$

where D is a discriminant score, B_{o} is an estimated constant, B_n are the estimated coefficients, and X_n are the variables. Based on this discriminant function score, an observation is classified into the appropriate group.

In this study, MDA is applied to the research data in order to characterize the group differences and to classify the banks group membership which are not known. Initially, Box's M-test performed to test the validity of the presumption of equality of group covariance matrices on the data set. According to the results of Box's M-test, group covariance matrices are not homogenous (Box's $M = 186.26$, $p \leqslant 0.001$). This means that the use of quadratic discriminant analysis on the data which does not presume the homogeneity of the group covariance matrices is appropriate.

The second method employed in the study is K-Means Cluster Analysis (CA) which attempts to classify a set of observations into groups like MDA. However, unlike MDA, neither the number of groups nor the group memberships are known in CA. CA attempts to identify homogeneous groups of observations based on the selected characteristics using an algorithm. This algorithm requires the researcher to specify the number of clusters. The units are divided into k cluster, where the calculation of squares in clusters is to be the minimum. If each of $X_1, X_2, \ldots, X_n$ values of p differential observation vectors are considered as points in the multidimensional X space, and in the same space where $a_{1n}, a_{2n}, \ldots, a_{kn}$ are chosen as cluster center for each unit; in accordance with $W_n = 1/n[\sum|X_i - a_{jn}|]$ rule the units are appointed to the nearest cluster (Tatlidil, 1996).

LRA is a form of regression which is used when the dependent is a dichotomy and the independents are of any type. In LRA models, the dependent variable is usually binary which can take the value 1 with a probability of success $P(Z_i)$, or the value 0 with probability of failure $1 - P(Z_i)$. The relationship between predictor independent variables and binary dependent is expressed with the following non-linear function:

$$P(Z_i) = \frac{e^{Z_i}}{1 + eu^{Z_i}} = \frac{1}{1 + eu^{-Z_i}} \tag{2}$$

where $P(Z_i)$ is a cumulative probability function that takes values between 0 and 1.

$$Z_i = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + \cdots + \beta_m F_m$$

where β_0 is the constant of the equation and, β_m are the coefficient of the predictor variables.

LRA aims to correctly predict the group of outcome for individual observations using the most parsimonious model. A model is created that includes all predictor variables that are useful in predicting the response variable.

4. Experimental results

Since the effectiveness of neural network techniques and SVMs can be affected by their parameters, a number of experiments with different levels of their parameters and different activation and kernel functions are carried out. Table 5 provides a summary for performance results of different methodologies with their best topologies.

The results for MLP showed that the whole data set with 20 pure input variables gives the most accurate classification results. The topology of the best MLP network consisted of 5 hidden layers with 30 neurons for each. The sigmoid activation function was employed in all layers of MLP. MLP correctly classified 100% of the banks in the training data set, and 95.5% of the banks in the validation set. These results mean that MLP accurately classified all of the input patterns of training data set and most of the validation data set. The performance of MLP can be considered as satisfactory.

In CL and SOM, the most accurate classification results were obtained by the topology which used the whole data set with 20 input variables normalized to z-score. Both CL and SOM networks were stabilized after 2000 epochs. CL and SOM provided similar classification performance. The performance of CL for training and validation data sets was found 58.14% and 68.18%, respectively while the related performance of SOM was 58.14% and 63.13% respectively. These results are not satisfying compared with the results of MLP.

The best topology and results of LVQ are different from the other neural network architectures. The LVQ yielded its best classification results with reduced and normalized data set. The training and validation performance of LVQ was found 83.72% and 100% respectively.

Four different kernel functions; linear, polynomial, radial basis and sigmoid are separately tested on both pure and normalized data sets with a stopping criteria value of 0.001. SVMs yielded its best performance with a third degree polynomial kernel function using the normalized data set. The obtained kernel function is as follows:

$$K(x_i, x_j) = (2x_i^\mathrm{T} x_j)^3$$

where x_i, x_j are vectors in the input space, x_i^T implies the transpose of vector x_i, using the above polynomial kernel function. SVMs correctly classified the 95.34% of banks in the training set and 90.90% of banks in the validation set.

Based on the results of factor analysis presented in the previous section, in the experiments where multivariate statistical methods are tested, seven factors were employed as predictor variables. In MDA experiments, a canonic discriminant function which increases the grouping ability and minimizes Wilks' Lambda was obtained. The eigenvalue (0.654) shows that the estimated discriminant model has quite high discriminating ability. Canonical correlation (0.629) is the measure of degree of association between D_i-scores and the grouping variable. The Wilks' Lambda value (0.605) shows the statistical importance of discriminant function or the quality of categorizing units into groups. The smaller this value the bigger the categorizing power of functions. The categorizing power of the function is quite high ($p = 0.009$). As a result of MDA experiments, the following discriminant model was obtained:

Table 5
Performance results for training and validation of prediction techniques

Prediction model	Data set	Training performance (%)	Validation performance (%)
Multi-layer perceptron (MLP)	Pure with 20 ratios	100.00	95.50
Competitive learning (CL)	Normalized with 20 ratios	58.14	68.18
Self-organizing map (SOM)	Normalized with 20 ratios	58.14	63.63
Learning vector quantization (LVQ)	Normalized with 9 ratios	83.72	100.00
Support vector machines (SVMs)	Normalized with 20 ratios	95.34	90.90
Multivariate discriminant analysis (MDA)	Seven factors	88.37	68.18
K-means cluster analysis (CA)	Seven factors	86.04	81.81
Logistic regression analysis (LRA)	Seven factors	86.04	81.81

$$D_i = 0.056 + 0.117F_1 + 1.189F_2 - 1.461F_3 - 0.185F_4 + 0.478F_5 + 0.166F_6 + 0.167F_7$$

In estimating the model, the SPSS program adjusted the dividing point to a cut-off value of zero. Banks with D_i-scores above zero were classified into the non-failed group, whereas banks with D_i-scores below zero were classified into the failed group. The classification accuracy rate of the model was 88.37% in the training set and 68.18% in the validation set.

In CA, to decide which variables will be taken into consideration and which will not, an Analysis of Variance (ANOVA) was employed. The results are given in Table 6. Table 6 shows that C1 is significant at the 5% level. C4 and C5 are also significant at 1% level. According to these variables there is a meaningful difference between clusters. Therefore, C1, C4 and C5 variables are taken into analysis. CA predicted the 86.04% of failure status of the banks in the training set and 81.81% of the banks in the validation set.

The results of LRA experiments are summarized in Table 7 below:

Table 7 shows that the factor F_2 is significant at the 5% level while the factors F_4, F_5 and F_7 are also significant at the 10% level. The estimated logistic regression model is presented below:

$$Z_i = -1.216 - 1.637F_1 - 3.770F_2 + 5.407F_3 + 2.116F_4 - 3.016F_5 - 2.813F_6 - 1.2433F_7$$

The statistical results for the above LRA model (Log-Likelihood = −13.544; $G = 31.940$; sd = 7; $p = 0.000$) means that the estimated model is meaningful. A bank is classified to the failed or non-failed group according to the estimated logistic model, based on a cut-off probability of 0.50 and calculated failure probability ($P(Z_i)$). The classifications were realized by the following procedure:

If $P(Z_i) < 0.50$, the bank is classified to the non-failed group.

If $P(Z_i) \geqslant 0.50$, the bank is classified to the failed group

LRA correctly predicted 86.04% of the banks in the training set and 81.81% in the validation set.

Prediction techniques yielded different performances in training and validation data sets. The most accurate prediction in training data set was obtained using MLP, while CL and SOM provided the worst performance. The performance of SVMs in training set outperformed other techniques but MLP. On the other hand, the multivariate statistical models have the approximate performance in the training set.

More realistic performance evaluation can be made using the results of the validation case. Although the most accurate classification was obtained by MLP in training set, the most accurate predictions in validation set are obtained by LVQ. LVQ model accurately classified all of the banks in the validation set into their groups. MLP followed LVQ in the prediction performance of validation data. The multivariate statistical methods provided nearly the same performance in the validation set. Results show that as learning algorithms, some neural network architectures and SVMs outperform the multivariate statistical methods. According to the results, MLP and LVQ can be considered as the most successful prediction models tested.

Table 6
ANOVA results of CA

	Cluster		Error		F	Sig.
	Mean square	df	Mean square			
C1	6.380	1	0.915	63	6.975	0.010
C2	0.076	1	10015	63	0.075	0.785
C3	0.930	1	10001	63	0.929	0.339
C4	17.024	1	0.746	63	22.831	0.000
C5	17.876	1	0.732	63	24.417	0.000
C6	0.000	1	1.016	63	0.000	0.988
C7	1.433	1	0.993	63	1.443	0.234

Table 7
Results of LRA experiments

Predictor	Coefficient	Standard error	Z-statistic	Significance	Odds ratio
Constant	−1.216	1.062	−1.15	0.252	–
F_1	−1.637	1.826	−0.90	0.370	0.19
F_2	−3.770	1.846	−2.04	0.041	0.02
F_3	5.407	3.759	1.44	0.150	223.02
F_4	2.116	1.170	1.81	0.071	8.30
F_5	−3.016	1.629	−1.85	0.064	0.05
F_6	−2.813	1.720	−1.64	0.102	0.06
F_7	−1.2433	0.7257	−1.71	0.087	0.29

5. Conclusions

This research aimed to apply and evaluate four different neural network models, support vector machines and three multivariate statistical methods to the problem of predicting bank failures. Based on the experimental results, the following conclusions can be made: First of all, the research data applied to the techniques is very important for effective predictions. The performances of various techniques differentiate with respect to the form of data set applied. On the other hand, since different prediction performances are obtained in training and validation data sets, it is difficult to adopt a unique technique for this problem. As many studies in a number of fields reported, the superiority of MLP in prediction problems is proven in this research again. As a newly developed learning algorithm, SVM outperformed most of other techniques employed in the research. Although MLP and LVQ neural network architectures are found as the most successful prediction models in the experiments, the prediction performances of SVMs and multivariate statistical methods are also satisfying.

Appendix

See Table A.1.

Table A.1
Banks taken over by the SDIF and current status thereof

Banks	Date of Transfer	Current Status	
Merged			
Egebank	December 21, 1999	Merged into Sumerbank on January 26, 2001	
Yurtbank	December 21, 1999	Merged into Sumerbank on January 26, 2001	
Yasarbank	December 21, 1999	Merged into Sumerbank on January 26, 2001	
Bank Kapital	October 27, 2000	Merged into Sumerbank on January 26, 2001	
Ulusal Bank	February 28, 2001	Merged into Sumerbank on April 17, 2001	
Interbank	January 07, 1999	Merged into Etibank on June 15, 2001	
Esbank	December 21, 1999	Merged into Etibank on June 15, 2001	
Iktisat Bank	March 15, 2001	Its banking and deposit taking license was revoked as of December 7, 2001 and the liquidation process was initiated. Upon the resolution adopted in the General Assembly Meeting on April 04, 2002 the liquidation decision was revoked and the Bank was merged under Bayindirbank	
Kentbank	July 09, 2001	Its banking and deposit taking license was revoked as of December 28, 2001 and the liquidation process was initiated. Upon the resolution adopted in the General Assembly Meeting on April 04, 2002 the liquidation decision was revoked and the Bank was merged under Bayindirbank	
EGS Bank	July 09, 2001	Its banking and deposit taking license was revoked as of January 18, 2002 and merged with Bayindirbank as of the same date	
Etibank	October 27, 2000	Its banking and deposit taking license was revoked as of December 28, 2001 and the liquidation process was initiated. Upon the resolution adopted in the General Assembly Meeting on April 04, 2002 the liquidation decision was revoked and the Bank was merged under Bayindirbank	
Toprakbank	November 30, 2001	Its banking and deposit taking license was revoked as of September 30, 2002 and merged with Bayindirbank as of the same date	
Pamukbank	June 19, 2002	In accordance with the Act No. 5230 "Transfer of Pamukbank Turk Anonim Sirketi to Turkiye Halk Bankasi A.S. and Act Concerning Making Changes in Some Acts" it was transferred to Turkiye Halk Bankasi A.S. on November 12, 2004	
Sold banks			
Bank Ekspres	December 12,1998	It was sold to the Tekfen Group on June 30, 2001. Merger of Bank Ekspres A.S. with Tekfen A.S. was approved by BRSA on October 18, 2001. It carries on its activities as Tekfenbank A.S	
Demirbank	December 06, 2000	A share transfer agreement was signed with HSBC Bank Plc. on September 20, 2001 and actual share transfer was realized on October 30, 2001	
Sumerbank	December 21, 1999	Merged Sumerbank was sold to the OYAK Group on August 9, 2001. The transfer of Sumerbank to Oyakbank A.S. was registered on January 11, 2002. It carries on its activities as Oyakbank A.S	
Sitebank	July 09, 2001	A share transfer agreement was signed with Novabank on December 20, 2001 and share transfer was realized on January 25, 2002	
Tarisbank	July 09, 2001	The share transfer agreement regarding its transfer to Denizbank A.S. was signed on October 21, 2002 and actual share transfer was completed on October 25, 2002. Merger of Denizbank A.S. with Tarisbank was approved by the BRSA on December 19, 2002 and merger was completed on October 27, 2002	
Banks under liquidation			
Turkbank	January 06, 1997	Pursuant to the Resolution No. 346 dated June 15, 2001 of BRSA, license of Turkbank to perform banking activities and accept deposits were revoked as of July 1, 2001 and within the scope of the Articles concerning dissolution and transfer of the Turkish Commercial Code and the Article 18 of the Abolished Bank Acts and the bank master agreement, the liquidation of the bank was decided to be realized. Upon the Resolution date August 9, 2002 of the Extraordinary General Meeting and registered on August 14, 2002, the liquidation transaction of the bank is continuing	
Bayindirbank (Birlesik Fon Bankasi)	July 09, 2001	It is determined as a bridge bank to carry out the function of asset management and bank's title designated in main contract was changed as "Birlesik Fon Bankasi A.S." in accordance with the Article No. 109 of the Banking Law No. 5411 and the Resolution No. 515 dated December 7, 2005 of the Fund Board	
The banks of which operating permission has been revoked and for which a bankruptcy decision has been adopted			
Banks	Date on which the operating permission revoked	Date of bankruptcy decision	Current status
The banks of which operating has been revoked according to the abolished banks Act No. 4389			
Kibris Kredi Bankasi	September 27, 2000	August 23, 2004	Bankruptcy of the bank has been judged pursuant to the Decree No. 2002/590 of the Istanbul Commercial Court of First Instance on August 23, 2004. Its liquidation is going on
Imar Bankasi	July 03, 2003	June 08, 2005	Bankruptcy of the bank has been judged pursuant to the Decree adjudicated with the File No. 2004/132 of the Istanbul Commercial Court of First Instance on August 08, 2005. Its liquidation is going on

Table A.1 (*continued*)

Banks	Date on which the operating permission revoked	Date of bankruptcy decision	Current status
The banks of which operating has been revoked according to the abolished banks Act No. 3182			
Marmara Bank	April 20, 1994	June 05, 1995	Bankruptcy of the bank has been judged pursuant to the Decree No. 1994/1425 of the Istanbul Commercial Court of First Instance
TYT Bank	April 11, 1994	December 2, 1996	Bankruptcy of the bank has been judged pursuant to the Decree No. 1994/1402 of the Istanbul Commercial Court of First Instance
Impex Bank	April 23, 1994	October 22, 1996	Bankruptcy of the bank has been judged pursuant to the Decree No. 1994/1395 of the Istanbul Commercial Court of First Instance

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