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A Comparison of Various Artificial Intelligence Methods in the Prediction of Bank Failures

Halil Ibrahim Erdal · Aykut Ekinci

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Abstract The strong relationship between bank failure and economic growth attaches far more importance to the predictability of bank failures. Consequently, numerous statistical prediction models exist in the literature focusing on this particular subject. Besides, artificial intelligence techniques began to attain an increasing level of importance in the literature due to their predictive success. This study distinguishes itself from the similar ones in the sense that it presents a comparison of three different artificial intelligence methods, namely support vector machines (SVMs), radial basis function neural network (RBF-NN) and multilayer perceptrons (MLPs); in addition to subjecting the explanatory variables to principal component analysis (PCA). The extent of this study encompasses 37 privately owned commercial banks (17 failed, 20 non-failed) that were operating in Turkey for the period of 1997–2001. The main conclusions drawn from the study can be summarized as follows: (i) PCA does not appear to be an effective method with respect to the improvement of predictive power; (ii) SVMs and RBF demonstrated similar levels of predictive power; albeit SVMs was found to be the best model in terms of total predictive power; (iii) MLPs method stood out among the SVMs and RBF methods in a negative sense and exhibits the lowest predictive power.

Keywords Bank failure · Support vector machines · Multilayer perceptrons · Radial basis function neural network · Principal component analysis

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H. I. Erdal · A. Ekinci (✉)
Development Bank of Turkey, Ankara, Turkey
e-mail: aykutekinci@gmail.com

1 Introduction

A well-functioning banking sector, which constitutes a major portion of the entire financial system, is one of the most crucial factors to achieve sustainable economic growth. Many countries, USA in particular, endured the most recent cases of economic losses inflicted by bank failures during the Global crisis of 2008. Turkey experienced similar troubles on its own during the economic crisis of 1999 that was induced by the arising Asian financial crisis, as well as the liquidity crisis of November 2000 and the ensuing February 2001 financial crisis. During the course of 2001 financial crisis in Turkey, Bank Kapital Turk, Etibank, Demirbank, Iktisat Bank, Tarisbank, Bayındırbank, EGSbank, Kentbank, Sitebank and Toprakbank; and during the course of 1999 economic crisis, Bank Ekspres, Egebank, Esbank, Interbank, Sümerbank, Yasarbank and Yurtbank were transferred to the savings deposit insurance fund (SDIF). In the meantime, the operating losses of publicly financed banks were indemnified, their capital structures were was consolidated and their operations were restructured (see BRSA 2009). Eventually, Turkey took significant lessons from the crisis and proceeded to enact new laws and regulations concerning the financial sector. As a matter of fact, Turkey turned out to be among the least severely affected countries from the recent Global crisis.

The strong relationship between bank failures and economic growth makes the predictability of bank failures ever more important. Several statistical prediction models exist in the literature focusing on this subject. Besides, artificial intelligence techniques began to attain a greater importance in the literature due to their predictive success. This study differentiates from the similar ones in the sense that it compares three different artificial intelligence methods against each other, namely support vector machines (SVMs), radial basis function neural network (RBF-NN) and multilayer perceptrons (MLPs), as well as subjecting the explanatory variables to principal component analysis (PCA). The dataset of this study encompasses 37 privately owned commercial banks (17 failed, 20 non-failed) that were operating in Turkey for the period of 1997–2001.

The rest of this article is organized into five additional sections. In the Sect. 2 of this study, a review of the related literature is presented. The Sect. 3 includes an introduction to SVMs, RBF-NN and MLPs methods, while the dataset used is presented in Sect. 4. In the Sect. 5, the findings are summarized. Lastly, the Sect. 6 includes the conclusions and final assessments.

2 Literature Review

The models used in the prediction of bank failures are divided into two main classes of methods, namely statistical methods and intelligent methods. The studies focusing on the prediction of bank failures by the assistance of statistical methods date back to 1970s, whereas studies employing intelligent methods originated in 1990s. The statistical methods comprise of (linear, multivariate and quadratic) discriminant analysis, factor analysis and logistic regression methods. On the other hand, intelligent methods comprise of artificial neural networks, evolutionary approaches, operations research, hybrid intelligent methods, fuzzy logic and SVMs etc.

The statistical prediction models concerned with bank failures date back to 1970s. Sinkey (1975) was the first to utilize multiple discriminant analysis in the prediction of bank failures. Meyer and Pifer (1970) and Martin (1977) used logistic regression analysis, while West (1985) recorded that a model based on the combined application of factor analysis and logistic regression analysis yielded better results. Lastly, Kolari et al. (2002) developed an early warning model to predict the failure of large-cap commercial banks in the US economy by employing logit analysis and trait recognition methods.

Intelligent methods are increasingly preferred instead of statistical methods as a virtue of their superior predictive success with respect to the prediction of bank failures. One of the first studies in which the prediction of bank failures was performed via various statistical methods and then compared against ANNs was conducted by Tam (1991). The author attempted to predict the bank failures in the state of Texas a year or two in advance by the assistance of various methods. Consequently, Tam concluded that the predictive power of back-propagation artificial neural networks (BPANN) model proved to be superior to any of the discriminant analysis, factor analysis, logistic analysis, and k-nearest neighbor algorithm also used in his study. Tam and Kiang (1992) compared the predictive powers of linear discriminant analysis, logistic regression, K-nearest neighbor analysis, Interactive Dichotomizer 3 (ID3), forward-feed artificial neural networks (FFANN), and BPANN models. Accordingly, they similarly concluded that the BPANN model generated the most favorable results. Olmeda and Fernandez (1997) also recorded that BPANN yielded the best prediction outcomes according to their study on Spanish commercial banks, followed by logit and discriminant analyses. Bell (1997) recorded that evaluating as a whole, ANNs perform better than logistic regression analysis in the prediction of commercial bank failures. Finally, Swicegood and Clark (2001) similarly came to the conclusion that ANNs exhibit a higher predictive power compared to discriminant analysis according to their study on the US banks.

The literature concerning the examination of bank failures in Turkey through the employment of artificial neural networks is quite young. Canbas et al. (2005) conducted a study on a total of 40 private commercial banks, of which 21 had eventually failed, for the period of 1997–2003. The researchers used discriminant analysis, logit and probit methods, and also established an integrated early warning system. The prediction accuracy pertaining to financial solvency of banks at period $t-1$ was found to be 90, 87.5 and 87.5 % for discriminant, logit and probit analyses, respectively. Benli (2005) comparatively used both logistic regression and ANNs methods in the prediction of bank failures. The author recorded that with respect to general classification success, the accurate classification rates for the ANNs model and logistic regression model are 87 and 84.2 %, respectively. Additionally, the prediction accuracy for the ANNs model concerning the failed banks is 82.4 %, while the corresponding rate is 76.5 % for the logistic regression model. As a result, it was inferred that the ANNs model possesses a superior predictive power than logistic regression model with respect to financial failures. Çinko and Avcı (2008) investigated the applicability of CAMELS rating system in the supervision of Turkish Commercial Banking system by studying those banks devolved to SDIF as well as those that remained solvent for the period of 1996–2001. They employed discriminant analysis, logistic regression and ANNs models in their study. The authors then recorded that in light of the obtained results, it could be stated that ANNs models yielded better results relative to the discriminant analysis and logistic regression models; however, the findings were still far from being satisfactory considering the low level of correct classification rates.

SVMs is a quite new methodology among the group of intelligent methods. In recent years, the area of usage for SVMs increasingly expanded. For instance, image recognition (Kilic et al. 2008), medical imaging (Gorgel et al. 2008), forecasting financial time series (Kim 2003), electric load forecasting (Pai and Hong 2005), electric demand forecasting (Wang et al. 2009), credit rating (Lee 2007), rain forecasting (Hong 2008), and forecasting crude oil prices (Yu et al. 2008) are only a few examples among the countless fields of application for SVMs.

In the literature, only a few studies are present in which SVMs are used in the prediction of bank failures. Among them, Ravi et al. (2008) used a variety of intelligent methods in their study. The authors used 54 variables pertaining to 1,000 banks in total and used the data for years (t-1) and (t-2) to predict the likelihood of bank failure in year t; and the prediction accuracy was found to be 83.5 % for SVMs. Boyacıoglu et al. (2009) investigated bank failures in Turkey for 1997–2003 and divided the banks into two classes as healthy–unhealthy and utilized CAMELS variables comprised of 20 financial ratios. In their study, various artificial neural analysis techniques such as support vector machines and multivariate statistical methods were used and then a comparison of their predictive powers was conducted. Besides, a third degree polynomial kernel was used in the support vector machines. According to the results of the study, it was seen that SVMs and MLPs models led to better results compared to the multivariate statistical models. On the other hand, Ekinci and Erdal (2011) compared the accuracy of SVMs and ANNs to predict the bank bankruptcies. Their study incorporates 35 privately owned commercial banks operating in Turkey between 1996 and 2000. A prediction of bank failures via the SVM was made and the results were compared using MLPs. The study consists of three different models. In the first model, a 1-year data set is used while the second one uses a 2-year and the third uses a 3-year data set. A significant difference in favor of the SVMs compared with MLPs was observed in the prediction of non-failed banks as well the total accuracy. Accordingly, Model 1 and Model 2 were equally accurate as per both the SVMs and MLPs in terms of the classification of failed banks, whereas the MLPs yielded more accurate results in Model 3.

3 Methodology

3.1 Mathematical Model for the PCA

An input data matrix can be shown as:

$$x = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix} = (x_1, x_2, \dots, x_p) \tag{1}$$

where p indicates the number of attributes and n indicates the number of samples,. Presuming that there are **a** p number of principal components, namely $\boldsymbol{f}_1, \boldsymbol{f}_2, \ldots, \boldsymbol{f}_p$; then the following equations hold:

$$
\begin{aligned}
f_1 &= l_{11}x_1 + l_{21}x_2 + \ldots + l_{p1}x_p \\
f_2 &= l_{12}x_1 + l_{22}x_2 + \ldots + l_{p2}x_p \\
&\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
f_p &= l_{1p}x_1 + l_{2p}x_2 + \ldots + l_{pp}x_p
\end{aligned}
\tag{2}
$$

subject to; $\sum_{i=1}^{p} l_{ij}^2 = 1, j = 1, 2, \ldots, p$ and $cov(f_i, f_j) = 0, i \neq j, i, j = 1, 2, \ldots, p$, where $(l_{1i}, l_{2i}, \ldots\ldots, l_{pi})$ indicate the coefficient factors.

Moreover, f_1 is the highest variance in linear combination among the entire set of attributes, whereas f_2 is the highest variance in linear combination aside from f_1, and f_3 is the highest variance in linear combination independent of the prior two principal components; similarly the rest may be inferred by extending this logic.

It can be proven that the coefficient $(l_{1i}, l_{2i}, \ldots\ldots, l_{pi})$ is the eigenvector corresponding to the characteristic value λ_i of the covariance matrix v of x, where for $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots\ldots \succ 0$, and$var(f_i) = \lambda_i, \lambda_i / \sum_{i=1}^{p} \lambda_i$; is defined to be the contribution ratio of y_i, and thereby $\sum_{i=1}^{m} \lambda_i / \sum_{i=1}^{p} \lambda_i$ gives the cumulative contribution ratio of $y_1, y_2, , \ldots, y_m$.

Criteria for Determining the Number of Factors: Using one or more of the methods below, the researcher determines an appropriate range of solutions to be investigated. Furthermore, the selected methods may not always be in agreement. For instance, the Kaiser criterion may suggest five factors whereas the screen test may suggest only two, so the researcher may seek 3-, 4-, and 5-factor solutions to discuss each alternative in terms of its relation to the external data and theory.

Kaiser Criterion: The eigenvalues obtained from correlation matrix R are taken into consideration to determine the number of principal components in case of applying the Kaiser criterion, which stipulates the selection of only those principal components with eigenvalues greater than unity (Mardia et al. 1979, p. 224). This criterion is the most widely used decision making method in determining the number of principal components (Stevens 2002, p. 389).

Variance Explained Criteria: Some researchers simply use the rule of employing the sufficient number factors that would suffice to account for 90 % (sometimes 80 %) of the variation. In case the researcher's objective emphasizes parsimony (explaining variance with as few factors as possible), the threshold could be as low as 66.7 % (2/3). As a result, it is desired that the greatest portion of the variance could be explained by deploying the lowest possible number of principle components (see Bandalos and Boehm-Kaufman 2009; Kachigan 1986).

3.2 Radial Basis Function Neural Networks

A RBF-NN is a type of a feed-forward neural network comprised of three layers: namely, input, hidden and output layers. Even though the computations between input and hidden layers are nonlinear, they are linear between hidden and output layers. An

RBF-NN can generate both regression and classification models. The final output is a weighted sum of the outputs of the hidden layer, given by the equation below:

$$\hat{y}(t) = \sum_{i=1}^{n} w_i \phi \left(\| u(t) - c_i \| \right) \tag{3}$$

where $u(t)$ is the input, $\phi(.)$ is a nonlinear radial basis function,$\|.\|$ denotes the norm, c_i indicates center of the radial basis function, and finally w_i is the input's weight. An RBF-NN takes the inputs and the hidden units as individual points in space. The activation of a hidden unit depends on the distance between the point for that hidden unit and the point in space which represents the input values. This distance is then converted into a similarity measure by the radial function. There are plenty of radial functions for activation such as Gaussian, multiquadric, inverse-multiquadric and Cauchy. The most commonly used radial function among them is the bell-shaped Gaussian radial filter given by the equation below:

$$h(x) = \exp\left(-\frac{(x-c)^2}{\beta^2} \right) \tag{4}$$

where c is the center and β is the radius.

3.3 Support Vector Machines (SVM)

The simplest classification problem is the two-class linear separable case. Assume that there is a training set which consists of "n" number of points.

$$(x_1, y_1), \ldots, (x_n, y_n), \quad x_i \in R^d, \ y_i \in \{-1, +1\} \tag{5}$$

Suppose that there are some hyperplanes separating the two classes, which can be shown by the following equation:

$$w.x + b = 0 \tag{6}$$

where w is the weight vector orthogonal to the hyperplane, and b is the threshold value. In the simplest linearly separable case, the "largest margin" is being seeked, where the margin borders can be formulated as:

$$y_i(w.x_i + b) \geq 1, \quad i = 1, \ldots, l \tag{7}$$

The quantity given by Eq. 8 below must be minimized to determine the optimal hyperplane:

$$1/2 \, \|w\|^2 \tag{8}$$

subject to Eq. 7, where $\|w\|$ is the Euclidean norm of w. This quadratic optimization problem can then solved with Lagrange Multipliers as shown below:

$$\text{Minimize } L(w, b, \alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i [y_i (w.x + b) - 1] \tag{9}$$

Equation (9) is a Lagrangian where w and b are the primal variables and α_i is the dual variable. At this stage, the problem is reduced to a dual optimization problem, which can be stated in the form of objective function shown below:

$$\text{Maximize } L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i x_j) \tag{10}$$

subject to the constraint $\sum_{i=1}^{l} \ \alpha_i y_i = 0\alpha_i \geq 0, \ i = 1, \ldots, l$

To indicate the measure of misclassification errors, a new term called "slack variables $(\xi_i)''$ is introduced as given below:

$$y_i (w.x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 10, \quad i = 1, \ldots, l \tag{11}$$

At this stage, a soft margin optimal separating hyperplane can be calculated as follows:

$$\text{Minimize } P = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} \xi_i \tag{12}$$

C is a given value which balances the margin maximization and training error minimization. In many cases, the problems are not linear, hence the training data can be mapped from the input space to a high dimensional feature space. Thus, the problems can be solved through a linear optimal separating hyperplane:

$$f(x) = \sum_{i=1}^{l} y_i \alpha_i (\phi(x) \cdot \phi(x_i)) + b \tag{13}$$

Generally, it is very hard to perform dot product $(\phi(x) \cdot \phi(x_i))$calculation, thus using Kernel functions instead can greatly simplify the calculations for the purpose of obtaining approximate results:

$$K(x, x_i) = \phi(x).\phi(x_i) \tag{14}$$

After inserting the Kernel function, the problem can be solved by the objective function below:

$$\text{Maximize } L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) \tag{15}$$

$$\text{Subject to the constraint } \sum_{i=1}^{l} y_i \alpha_i = 0, \quad 0 \leq \alpha_i \leq C, \quad i = 1, \ldots, l \tag{16}$$

3.4 Multilayer Perceptrons

A hidden layer exists between input and output layers, which makes y a nonlinear function of x. The variables$x_0, x_1, x_2, \ldots, x_f$, form the input layer; $H_0, H_1, \ldots, H_m$ form the hidden layer and y denotes the output of the neural network. As for the weights connecting the layers, w_{hi} connects input neuron i to the hidden neuron h and T_h connects hidden neuron h to the output layer. x_0 and h_0 denote the bias units for the input and hidden, respectively. The number of units in the hidden layer is taken to be half the number of features, with the purpose of achieving a suitable dimensionality reduction from f to 1.

At instance t, the real output y_t and the hidden layer output H_{ht} are found as:

$$H_h^t = sigmoid\left(\sum_{i=0}^{f} w_{hi}x_i^t + w_{h0}\right) \tag{17}$$

$$y^t = sigmoid\left(\sum_{h=0}^{m} T_h H_h^t + H_0\right) \tag{18}$$

The update rules are different from a single layer perceptron. There are two layers, so there are two update rules; one for updating w$_{hi}$and the other for updating T$_h$. The learning rate is initiated at 0.3/f and then gradually lowered as explained in the linear perceptron model. The update rules are as follows:

$$\Delta T_{ht} = \eta(d_t - y_t)y_t(1 - y_t)H_{ht} + \alpha\Delta T_{ht} - 1;\ h = 0, \ldots, m;\ H_0 = 1 \tag{19}$$

$$T_{ht} + 1 = T_{ht} + \Delta T_{ht} \tag{20}$$

$$\Delta w_{hit} = \eta(d_t - y_t)y_t(1 - y_t)T_{ht}H_{ht}(1 - H_{ht})x_{it} + \alpha\Delta T_{ht} - 1 \tag{21}$$

where $h = 0, \ldots, m$ and $i = 0, \ldots, n$; $H_0 = 1x_0 = 1$

$$w_{hit} + 1 = w_{hit} + \Delta w_{hit} \tag{22}$$

Training of the multilayer perceptron requires $O(e{*}n{*}f2)$updates, where e is the number of epochs to train the network, n is the number of instances, and$f$ is the number of features. The equation includes the$f2$term, because there are $m * f$ updates for the weights in the first layer and m updates in the second layer. As explained previously, m is equal to$f/2$. Consequently, the total number of updates is $f2/2 + f/2$, which in turn equals $O(f2)$. Multilayer perceptron models differ from other multivariate models in their nonlinear nature. With this model, a nonlinear split at a decision node can be obtained.

4 Data and Parameter Selection

The data used in the study was obtained from 37 privately owned commercial banks operating in Turkey between 1997 and 2001. Seventeen out of the 37 banks suffered

Table 1 Eigenvalues of the attributes

Attribute	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Code	WH	E	F	WK	H	U	N	V	B	WG
Eigenvalue	9.3	7.0	6.3	6.0	5.8	5.6	5.4	5.3	5.2	5.0
Cumulative % of variation explained	9.3	16.3	22.6	28.7	34.5	40.1	45.5	50.8	56.0	61.0
Attribute	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Code	D	WJ	Y	WI	K	S	W	R	WB	WC
Eigenvalue	4.5	3.9	3.5	2.8	2.3	2.1	1.7	1.7	1.6	1.6
Cumulative % of variation explained	65.5	69.5	72.9	75.8	68.8	80.2	81.9	83.6	85.3	86.9
Attribute	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
Code	A	M	WF	I	P	G	O	C	Z	T
Eigenvalue	1.6	1.6	1.3	1.2	1.1	1.1	1.0	1.0	0.6	0.6
Cumulative % of variation explained	88.5	90.1	91.4	92.6	93.7	94.8	95.8	96.8	97.4	98.1
Attribute	**31**	**32**	**33**	**34**	**35**					
Code	WA	J	WE	WD	L					
Eigenvalue	0.6	0.5	0.4	0.4	0.1					
Cumulative % of variation explained	98.6	99.1	99.5	99.9	100.0					

Note Please refer to Appendix 2 for the code explanations

financial failure while the remaining ones did not. Appendix 1 shows further information about the above mentioned banks. The variables used in the prediction of bank failure consist of 35 financial ratios determined by The Banks Association of Turkey in accordance with capital, asset quality, management, earnings, liquidity, sensitivity ratios (CAMELS) system. The financial ratios used are shown in Appendix 2. The year when failed bank was taken over by the SDIF was considered as (t + 1); and the first year right before the bank failure occurred is represented by (t). The financial ratios of failed banks in year (t) change according to the date of failure. For example, as shown in Appendix 2, Bank Ekspres failed in 1998 and hence the value of (t) for this bank is 1997. (t) for the non-failed banks stand for the year 2000.

The 35 explanatory variables were subjected to PCA, and thereby it was attempted to determine the set of relevant attributes in bank failures. As per the variance explained criterion, the 12 attributes whose sum of eigenvalues exhibit an explanatory power of 66.7 % or greater in terms of the cumulative percentage of explained variation are chosen; while 28 attributes were taken as the set of relevant attributes as per the Kaiser criterion since their eigenvalues were greater than or equal to 1 (see Table 1). The set of relevant attributes were determined in accordance with PCA; nevertheless, model analyses were carried out until the nine attributes possessing the weakest explanatory power were discarded from the analysis, hence testing the effectiveness of PCA over the results. Consequently, 26 different prediction models were devised for each of the SVMs, RBF-NN and MLPs methods. In this study, a principal component analysis was also performed using Ranker search as the search method.

Dimensionality reduction was accomplished through the selection of sufficient number of eigenvectors to account for a given percentage of the variance in the original data, such as 95 % chosen for the scope of this study. Choosing the correct settings for the metaparameters C and ε as well as the kernel parameters are crucial for the estimation accuracy of a SVM. In this study, the SVMs' parameters were as follows: The kernels were RBF kernel and Poly kernel; the complexity parameters were 1, 5 and 10; the epsilon values were 1.0E-11, 1.0E-12 and 1.0E-13; and finally the exponents were 1, 2 and 3. The experiments indicated that the best parameter configuration for this technique was as follows: Poly kernel (K(x,y)=<x,y>^p), which was chosen to be the core function for SVMs; the complexity parameter was 1, epsilon was 1.0E-12, and the exponent was 1. The MLPs' parameters tested in the proposed model included the following: the number of hidden layers were 1, 2, and 3; the number of hidden neurons were 35 and 70 for each hidden layer; the learning rate was 0.2, 0.3 and 0.4; the momentum factor was 0.2, 0.3, and 0.4; and the training time was 500; 1,000; and 1,500. The best network parameters were as follows: the number of hidden layers was 2; the number of hidden neurons was 35 for each layer; the number of the learning rate was 1.0; the momentum factor was 0.3; and the training time was 5,000. The data set was used in several experiments to obtain the suitable parameters for RBFs. The parameters for RBF-NN were as follows: the minimum standard deviations were 0.1, 0.2 and 0.3 the Ridge values were 1.0 E-8, 1.0 E-9 and 1.0 E-10; the number of clusters were 1, 2 and 3, finally the maximum number of iterations were 1 and 5. The best parameter values then used to predict bank failures for RBF-NN were as follows: the minimum standard deviation was 0.1, the Ridge value was 1.0 E-8, the number of clusters was 2, and finally the maximum number of iterations was 1.

5 Results

This study conducted a comparison of three distinct artificial intelligence methods; namely SVMs, RBF-NN and MLPs, with respect to their utilization in the prediction of bank failures; and subjects the explanatory variables to PCA during the course of this comparison.

Table 2 presents the prediction results obtained by all three methods for the 26 models as can be seen in the "model no." row. The 1st model utilizes all 35 of the explanatory attributes, while the 8th and 24th models present the analysis results obtained with 28 and 12 variables (shown bold in Table 2) selected as per the variance explained and Kaiser criteria, respectively. The "set of attributes" row denotes the number of employed explanatory attributes in descending order of explanatory power as per PCA. The "inaccurate predictions (non-failed)" row shows the number of banks predicted by the method to fail but eventually did not fail; the" inaccurate predictions (failed)" row shows the number of banks predicted by the model to not fail but eventually did fail; and finally the "inaccurate predictions (total)" row shows the number of total false predictions by the model. The "accuracy ratio (non-failed) %" row gives the percentage of correctly predicting the non-failed banks; the "accuracy ratio (failed) %" row gives the percentage of correctly predicting the failed banks; and finally the "accuracy ratio (total) %" row gives the overall percentage of correct predictions by the model.

SVMs and RBF-NN methods singlehandedly yielded the best results in terms of accurately predicting non-failed banks in 13 and 5 models, respectively; while SVMs

Table 2 Model analyses

Model no.	1	2	3	4	5	6	7	8	9	10	11	12	13
SVMs													
Set of attributes	35	34	33	32	31	30	29	**28**	27	26	25	24	23
Inaccurate prediction (non-failed)	1	1	2	3	3	4	4	**4**	3	3	3	3	3
Inaccurate prediction (failed)	3	3	3	3	5	5	5	**5**	5	6	5	5	5
Inaccurate prediction (total)	4	4	5	6	8	9	9	**9**	8	9	8	8	8
Accuracy ratio (non-failed) %	95	95	90	85	85	80	80	**80**	85	85	85	85	85
Accuracy ratio (failed) %	82	82	82	82	71	71	71	**71**	71	65	71	71	71
Accuracy ratio (total) %	89	89	86	84	78	76	76	**76**	78	76	78	78	78
MLPs													
Set of attributes	35	34	33	32	31	30	29	**28**	27	26	25	24	23
Inaccurate prediction (non-failed)	8	8	8	10	10	10	11	**10**	11	10	10	10	10
Inaccurate prediction (failed)	5	3	4	4	4	4	4	**5**	6	6	6	6	6
Inaccurate prediction (total)	13	11	12	14	14	14	15	**15**	17	16	16	16	16
Accuracy ratio (non-failed) %	60	60	60	50	50	50	45	**50**	45	50	50	50	50
Accuracy ratio (failed) %	71	82	76	76	76	76	76	**71**	65	65	65	65	65
Accuracy ratio (total) %	65	70	68	62	62	62	59	**59**	54	57	57	57	57
RBF-NN													
Set of attributes	35	34	33	32	31	30	29	**28**	27	26	25	24	23
Inaccurate prediction (non-failed)	3	3	3	2	3	3	2	**2**	3	4	3	3	3
Inaccurate prediction (failed)	3	3	3	5	5	5	5	**7**	6	6	6	6	6
Inaccurate prediction (total)	6		6	7	8	8	7	**9**	9	10	9	9	9
Accuracy ratio (non-failed) %	85	85	85	90	85	85	90	**90**	85	80	85	85	85
Accuracy ratio (failed) %	82	82	82	71	71	71	71	**59**	65	65	65	65	65
Accuracy ratio (total) %	84	84	84	81	78	78	81	**76**	76	73	76	76	76
Model no.	14	15	16	17	18	19	20	21	22	23	24	25	26
SVMs													
Set of attributes	22	21	20	19	18	17	16	15	14	13	**12**	11	10
Inaccurate prediction (non-failed)	2	2	2	3	1	1	2	2	5	3	**4**	4	6
Inaccurate prediction (failed)	5	5	5	6	5	5	5	5	5	5	**4**	5	4
Inaccurate prediction (total)	7	7	7	9	6	6	7	7	10	8	**8**	9	10
Accuracy ratio (non-failed) %	90	90	90	85	95	95	90	90	75	85	**80**	80	70
Accuracy ratio (failed) %	71	71	71	65	71	71	71	71	71	71	**76**	71	76
Accuracy ratio (total) %	81	81	1	76	84	84	81	81	73	78	**78**	76	73
MLPs													
Set of attributes	22	21	20	19	18	17	16	15	14	13	**12**	11	10
Inaccurate prediction (non-failed)	10	10	10	9	9	9	9	9	10	8	**4**	6	9
Inaccurate prediction (failed)	6	6	6	6	5	5	5	5	4	5	**5**	4	4
Inaccurate prediction (total)	16	16	16	15	14	14	14	14	14	13	**9**	10	13
Accuracy ratio (non-failed) %	50	50	50	55	55	55	55	55	50	60	**80**	70	55
Accuracy ratio (failed) %	65	65	65	65	71	71	71	71	76	71	**71**	76	76

Table 2 continued

Model no.	14	15	16	17	18	19	20	21	22	23	24	25	26
Accuracy ratio (total) %	57	57	57	59	62	62	62	62	62	65	**76**	73	65
RBF-NN													
Set of attributes	22	21	20	19	18	17	16	15	14	13	**12**	11	10
Inaccurate prediction (non-failed)	3	3	3	3	4	4	4	6	5		**4**	6	4
Inaccurate prediction (failed)	7	6	6	5	4	4	4	4	4	4	**4**	4	5
Inaccurate prediction (total)	10	9	9	8	8	8	8	10	9	8	**8**	10	9
Accuracy ratio (non-failed) %	85	85	85	85	80	80	80	70	75	80	**80**	70	80
Accuracy ratio (failed) %	59	65	65	71	76	76	76	76	76	76	**76**	76	71
Accuracy ratio (total) %	73	76	76	78	78	78	78	73	76	78	**78**	73	76

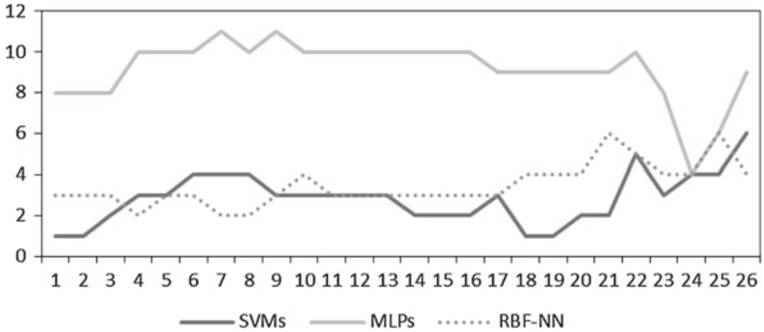

Fig. 1 Inaccurate prediction (non-failed)

and RBF-NN tied for the best prediction in 7 models. Finally, all three methods predicted the same number of non-failed banks in just 1 model. In this context, it is observed that SVMs proved to be superior to the other methods as a result of singlehandedly or jointly producing the best prediction in 21 out of the 26 models. It is seen that MLPs is clearly inferior compared to SVMs and RBF methods in terms of predicting non-failed banks (Fig. 1). It is also observed that PCA is not influential on the final results. The solutions conducted by an explanatory variable set of neither 28 nor 12 variables were able to improve the prediction performance. The only notable exception is the prediction by MLPs for a set of 12 explanatory variables. MLPs method exhibited a poorer predictive power for both the prior and the latter set of variables, while the number of unsuccessful predictions concerning the number of non-failed banks receded to four for the 12-variable solution set.

SVMs, RBF-NN and MLPs methods singlehandedly yielded the best results in terms of accurately predicting the failed banks in 8, 6 and 3 models, respectively; while SVMs and RBF-NN, SVMs and MLPs, and all three methods concurrently yielded the best prediction in 2, 2 and 2 models, respectively. On the whole, SVMs generated the best results in 17 models; whereas RBF-NN and MLPs were able achieve the best prediction in only 13 and 7 models, respectively. It is seen that the methods generate similar results in the prediction of failed banks and again, PCA was found to

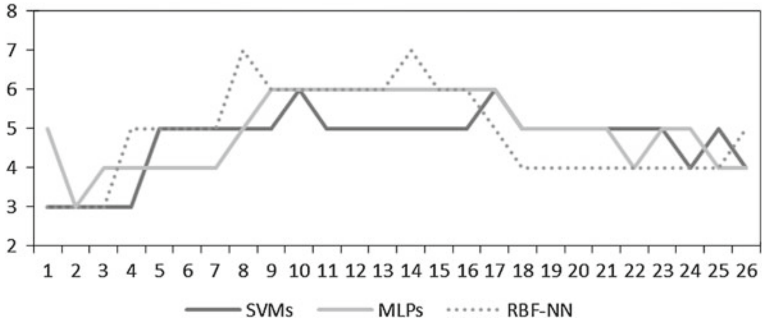

Fig. 2 Inaccurate prediction (failed)

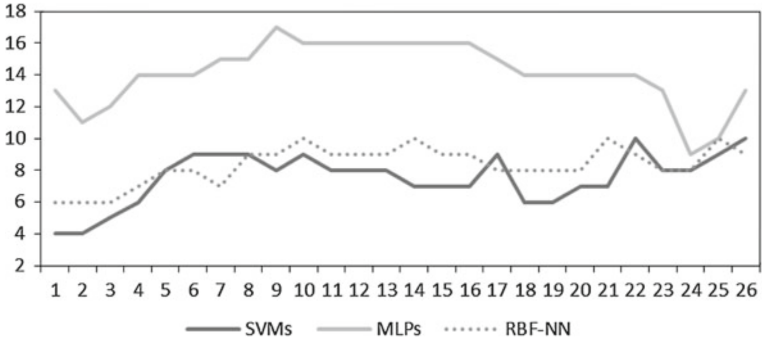

Fig. 3 Inaccurate prediction (total)

have no discernible effect on the outcomes (Fig. 2). In case of employing the entire set of variables (model 1), SVMs and RBF-NN methods were found to exhibit the highest predictive power.

SVMs and RBF-NN methods yielded the best results in terms of total percentage of correct predictions in 17 and 5 models, respectively; while SVMs & RBF-NN concurrently yielded the best prediction in 4 models. Here again, SVMs displayed the highest prediction accuracy in 21 models out of 26. As for the total prediction power, MLPs persisted to demonstrate the lowest predictive power as a result of its poor performance in the prediction of non-failed banks; while SVMs and RBF-NN continued to demonstrate similar levels of predictive power. Nonetheless, it is seen that SVMs stands out as the best model with respect to total prediction power (Fig. 3).

6 Conclusions

This study distinguishes itself from the similar ones in the sense that it carries out a comparison of three different artificial intelligence methods, namely SVMs, RBF-NN and MLPs; in addition to subjecting the explanatory variables to PCA. The dataset of this study encompasses 37 privately owned commercial banks (17 failed, 20 non-failed) operating in Turkey for the period of 1997–2001. In this study, though the set of explanatory attributes were determined in accordance with PCA; model analyses were conducted using down to 10 attributes possessing the highest explanatory power, thereby testing the effectiveness of PCA over the results. As a result, 26 different prediction models were created for each of the SVMs, RBF-NN and MLPs methods.

The fundamental conclusions drawn from the study with respect to the prediction of bank failures by the assistance of a particular set of artificial intelligence methods can be described as follows: (i) PCA was found to be ineffective for the purpose of improving the prediction performance; (ii) SVMs and RBF-NN demonstrated similar levels of predictive power with each other; nevertheless, SVMs was found to be the best model in terms of total predictive power; (iii) MLPs method diverges from the SVMs and RBFs methods as a result of poor outcomes and displays the lowest predictive power.

Appendix 1

See Table 3.

Table 3 Relevant information pertaining to the banks analyzed in the study

Bank name	Date of devolution to SDIF
Adabank	–
Akbank	–
Alternatifbank	–
Anadolubank	–
Bank Ekspres	December 12nd, 1998
Bank Kapital Türk	October 27th, 2000
Bayındırbank	July 9th, 2001
Birleşik Türk Körfez Bank	–
Demirbank	December 6th,2000
Denizbank	–
EGSbank	July 9th, 2001
Egebank	December 21nd, 1999
Esbank	December 21nd,1999
Etibank	October 27th, 2000
Finans Bank	–
İktisat Bank	March 15th, 2001
İnterbank	January 7th, 1999
Kentbank	July 9th, 2001
Koçbank	–
Tarisbank	June 9th, 2001
MNG Bank	–
Oyak Bank	–
Pamukbank	–
Sitebank	July 9th, 2001
Sümerbank	December 21nd, 1999

Table 3 continued

Bank name	Date of devolution to SDIF
Şekerbank	–
Tekstil Bank	–
Toprakbank	November 30th, 2001
Turkish Bank	–
Türk Dış Ticaret Bank	–
Türk Ekonomi Bank	–
Türkiye Garanti Bank	–
Türkiye İmar Bank	–
Türkiye İş Bank	–
Yasarbank	December 21nd, 1999
Yapı ve Kredi Bank	–
Yurtbank	December 21nd, 1999

Source SDIF http://www.tmsf.org.tr/bank.transfer.en

Appendix 2

See Table 4.

Table 4 The financial ratios used in the study (CAMELS)

Main ratio class	Ratios	Codes
Capital ratios (%)	(Equity + earnings)/total assets	A
	(Equity + total earnings)/(deposits & non-deposit liabilities)	B
	Net working capital/total assets	C
	(Equity + total earnings)/(total assets + non-cash loans)	D
	FX position/equity	E
Asset quality (%)	Total loans/total assets	F
	Non-performing loans/total loans	G
	Non-current assets/total assets	H
	FX Assets/FX liabilities	I
Liquidity (%)	Liquid assets/total assets	J
	Liquid assets/(deposits & non-deposit liabilities)	K
	FX liquid assets/FX liabilities	L
Profitability (%)	Net income (loss)/average T. assets	M
	Net income (loss)/average equity	N
	Net income (loss)/average share-in capital	O
	Income before tax/average total assets	P
	Provision for loan losses/total loans	R
	Provision for loan losses/total assets	S

Table 4 continued

Main ratio class	Ratios	Codes
Income-expenditure structure (%)	Net interest income after provision average T. assets	T
	Interest income/interest expenses	U
	Non-interest income/non-interest expenses	V
	Total income/total expenditure	Y
	Interest income/average profitable assets	Z
	Interest expenses/average interest costing assets	W
	Interest expenses/average non-profitable assets	WA
	Interest income/total income	WB
	Non-interest income/total income	WC
	Interest expenses/total expenses	WD
	Non-interest expenses/total expenses	WE
Activitiy ratios (%)	(Salaries and employee benefits + reserve for retirement)/T. assets	WF
	(Salary and employee bene. + res. for retire.)/no. of pers. (Billion TL)	WG
	Reserve for seniority pay/no. of personnel (Billion TL)	WH
	Operational expenses/total assets	WI
	Provisions except provisions for income tax/total income	WJ
	Provisions including ovisions for income tax/total income	WK

Source The banks association of Turkey, statistical reports, selected ratios http://www.tbb.org.tr/eng/Banka_ve_Sektor_Bilgileri/Istatistiki_Raporlar.aspx

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