Bankruptcy Prediction in Banks by Principal Component Analysis Threshold Accepting trained Wavelet Neural Network Hybrid

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Abstract - *This paper proposes new principal component analysis-wavelet neural network hybrid (PCA-TAWNN) architecture trained by Threshold Accepting (TA) algorithm to predict bankruptcy in banks. This architecture consists of an input layer, the principal component layer consisting of a few selected principal components, a hidden layer with wavelet activation function and finally an output layer with a sigmoid activation function. The effectiveness of PCA-TAWNN is tested on Turkish, Spanish and UK banks bankruptcy datasets and two benchmark datasets Wine and WBC. We observed that PCA-TAWNN convincingly outperformed other techniques in terms of Area under ROC curve (AUC) in 10-fold cross-validation.*

Key words - Bankruptcy Prediction, Principal Component Analysis, Wavelet Neural Networks, Threshold Accepting

1 Introduction

Over the past three decades several researchers made interesting contributions to predict business failure in banks and firms. It is observed that timely and correctly predicting the failure of a firm is of paramount importance specifically for financial institutions. Bankruptcy prediction for financial firms has been the extensively researched area since 1960's [1]. Creditors, auditors, stockholders and senior management are all interested in bankruptcy prediction because it affects all of them in the same way [2]. In the online methods on site examinations are conducted on banks' premises by regulatory authorities every 12-18 months as mandated by the Federal Deposit Insurance Corporation Improvement (FDIC) act of 1991. Regulators use a six part rating system referred to as CAMELS, which evaluates bank's financial health according to their basic functional areas viz., ***C****apital adequacy,* ***A****sset quality,* ***M****anagement expertise,* ***E****arnings strength,* ***L****iquidity,* and ***S****ensitivity to market risk*. This information is obtained from the bank's balance sheets. While CAMELS ratings clearly provide regulators with important information, Cole and Gunther [3] reported that these CAMELS ratings decay rapidly**.** Further, financial experts are a scarce and expensive resource. Hence, banks thought that it was better to apply off-line, computer based algorithms to determine bank's financial health. They turned out to be not only cheaper but also accurate.

Standard statistical techniques such as regression analysis, logistic regression have been used to analyze a company's financial data in order to predict the financial state of the company. However, this problem can also be solved using various intelligent techniques. The present work introduces a new hybrid PCA-TAWNN, which employs PCA and modified TAWNN in tandem. The rest of the paper is organized as follows. Section II reviews the related work in bankruptcy prediction of banks and firms. Section III presents the proposed PCA-TAWNN architecture. Section IV describes briefly the three bankruptcy datasets that are analyzed by the hybrid model. Results and discussions are presented in section V. Finally, section VI concludes the paper.

2 Literature review

Altman [1] pioneered the research in failure predictions of businesses. He employed financial ratios and Multilinear Discriminant Analysis (MDA) to predict financially distressed firms. While Korobow et al. [4] first applied a probabilistic approach to solve this problem, Karels and Prakash [5] rigorously investigated the normality conditions of financial ratios in the context of DA. Later, Pantalone and Platt [6] employed logistic regression. However, as is well-known, statistical techniques such as MDA have too restrictive assumptions like normality, which are rarely satisfied in practice. Hence researchers turned to non-parametric techniques, which cover the entire gamut of intelligent techniques. Later, statistical techniques like Logit Model [7],[8] and machine learning approaches such as BPNN [2],[9],[10]. Decision Tree [11], K-nearest neighbor and ID3 [12] are applied for failure prediction. Further, hybrid approaches like MDA assisted neural network, ID3 assisted neural network and a self-organizing map assisted neural network [13], MDA, case based reasoning and neural networks [14] are also proposed for predicting the bankruptcy in firms. Many of these studies reported superior performance of BPNN. Therefore, BPNN became an

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attractive alternative to statistical techniques for bankruptcy prediction.

The trend of hybridizing machine learning and statistical techniques continued. Olmeda and Fernandez [15] predicted bankruptcy in Spanish banks by considering the financial ratios presented in Table 1. They employed BPNN, logistic regression, multivariate adaptive splines (MARS), C4.5 and MDA in devising an ensemble system. They found that BPNN outperformed all other models in the stand-alone mode and the combination of neural network, logistic regression, C4.5 and MDA performed the best among all the combinations. Then, Alam et al. [16] showed that both the fuzzy clustering and self-organizing neural networks are promising tools to predict potentially failing banks. McKee [17] reported that rough set theory significantly outperformed a recursive-partitioning model in predicting bankruptcy. Ahn et al. [18] observed that their hybrid models combining rough sets and BPNN with feature selection and sample size reduction yielded better solutions compared to BPNN and DA for bankruptcy prediction in Korean firms.

Atiya [19] surveyed all the prediction techniques in this context and proposed more financial indicators, to design of a new neural network model**.** Further, Swicegood and Clark [20] compared DA, BPNN and human judgment in predicting bank failures. Shin and Lee [21] generated rules using genetic algorithm (GA) for bankruptcy prediction. Park and Han [22] concluded that K-NN weighted with analytical hierarchy process (AHP) outperformed other models for predicting bankruptcy in Korean firms. Cielen et al. [23] reported that data envelopment analysis (DEA) outperformed C5.0 and a combination of linear programming and discriminant analysis in predicting bankruptcy in Belgian banks. Tung et al. [24] proposed a new neuro-fuzzy system to predict bankruptcy in banks and concluded that the BPNN outperformed this neuro-fuzzy system. Andres et al. [25] reported that a variant of additive fuzzy systems outperformed discriminant analysis and logistic regression in predicting failure of Spanish commercial and industrial firms. Ryu and Yue [26] reported that isotonic separation outperformed BPNN, logistic regression and probit method. Shin et al. [27] concluded that SVM outperformed the BPNN in predicting corporate bankruptcy. Canbas et al. [28] proposed an integrated early warning system (IEWS) for detecting banks experiencing serious problems**.** Becerra et al. [29] reported that wavelet neural networks have advantages over the BPNN in corporate financial distress prediction.

Then, auto associative neural network [30], fuzzy rule based classifier (FRBC) [31], semi-online training algorithm for the radial basis function neural networks (SORBF1 and SORBF2) [32] hybrid of RBF Network with Logit Analysis [33], multiple ensembles of ANFIS, SVM, RBF, SORBF1, SORBF2, Orthogonal RBF and BPNN [34] reported better results compared to BPNN and others. Pramodh and Ravi [35] proposed modified great deluge algorithm trained auto associative neural network for bankruptcy prediction Further, Ravi et al. [36] developed a novel soft computing system based on BPNN, RBF, classification and regression techniques (CART), probabilistic neural network (PNN), and FRBC and PCA based hybrid techniques**.**

Then a comprehensive review of the works using statistical and intelligent techniques to predict bankruptcy in banks and firms during 1968-2005 [37] appeared. Later, , Ravi and Pramodh [38] reported that their threshold accepting trained principal component neural network (PCNN), without a formal hidden layer outperformed BPNN, threshold accepting trained neural network (TANN), PCA-BPNN and PCA-TANN. Then Sun and Li [39] applied weighted majority voting based ensemble of classifiers, Sun and Li [40] employed serial combination of classifiers and Li and Sun [41] developed an ensemble of case based reasoning classifiers to bankruptcy prediction. Most recently, Ramu and Ravi [42] proposed a new privacy preserving data mining technique to predict bankruptcy in banks. Then, Chandra and Ravi [43] applied FRBC preceded by a WNN based feature selection method to predict bankruptcy. Further, Chandra et al. [44] developed Support Vector machine-WNN hybrid (SVWNN) to predict bankruptcy in banks.

3 Proposed PCA-TAWNN

In the recent past, Ravi and Pramod [38], Ravisankar and Ravi [45] and Ravi and Pramod [46] respectively reported hybrid neural networks involving PCA, a kernel variation of PCA and nonlinear PCA for bankruptcy prediction. Also, it is found that WNN [47] yielded good results in predicting bankruptcy. Further it is noticed that TANN performed better compared to BPNN [38]. So the idea of exploring the generalization power of the TAWNN classifier together with the first few principal components (denoted by *npc*) extracted from PCA is worth investigating in bankruptcy prediction. Hence, in this paper, we propose novel hybrid architecture for bankruptcy prediction in banks involving PCA and a modified TAWNN (PCA-TAWNN) as depicted in Fig 1. In the figure, *nin* and *nhn* represent number of input nodes and number of hidden nodes respectively. The proposed hybrid consists of two major phases: (i) The first few principal components are chosen after performing PCA on the data matrix (ii) Then, they are fed as inputs to the modified TAWNN. Here, the original TAWNN (Vinaykumar et al.[48]) is modified by replacing the usual linear activation function by a sigmoidal activation function. At this juncture, it is worth mentioning the difference between PCNN and the proposed PCA-TAWNN. While PCNN follows the design and architecture of Multilayer perceptron, the proposed PCA-TAWNN follows that of wavelet neural network. Secondly, PCNN consists of 3 layers including input layer with a bias node in the PC layer, whereas PCA-TAWNN has 4 layers with no bias node in any layer. Thus, PCA-TAWNN has an extra hidden layer, which performs wavelet related computations by making use of Gaussian wavelet activation function. For more details on PCA and TAWNN, the reader is referred to Rawlings [49] and Vinaykumar et al. [48] respectively.

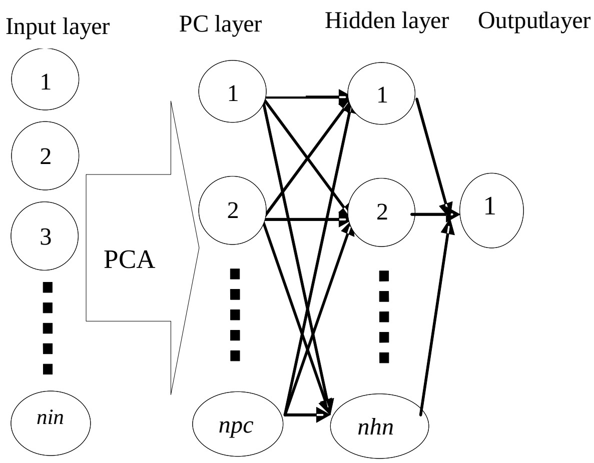

Fig.1.Proposed PCA-TAWNN Architecture

4 Dataset description

In this study, the effectiveness of our proposed hybrid is demonstrated on three bankruptcy datasets *viz.*, Turkish, Spanish and UK banks and two benchmark datasets *viz.*, Wine and WBC. Turkish banks' dataset is obtained from Canbas et al. [28], which is available at (http://www.tbb.org.tr/english/bulten/yillik/2000/ratios.xls). It has 40 banks where 22 banks went bankrupt and 18 banks are healthy. The Spanish banks' data is taken from Olmeda and Fernandez [15]. This dataset contains 66 banks where 37 went bankrupt and 29 healthy banks. The UK banks' data is taken from Beynon and Peel [50].This dataset consists of 60 samples out of which 30 are healthy and 30 are bankrupt. The financial ratios for all the banks are presented in Table **1**. Wine and WBC datasets are obtained from UCI machine learning repository (http://www.ics.uci.edu/~mlearn/). Wine dataset consists of 178 samples with 13 attributes representing three classes. WBC dataset consists of 683 samples with 9 attributes, where 444 samples belong to benign class and 239 samples belong to malignant class.

5 Results and discussions

We performed 10-fold cross validation throughout and the average results obtained are presented in Table 2-4. The results of the hybrid are compared with those of the previous studies conducted by the research group led by the second author. This comparison was possible because the same experimental design and the same folds were used in the 10-fold cross validation for all the techniques. The quantities employed to measure the quality of the classifiers are sensitivity, specificity and accuracy, which are defined as follows [51].

Table 1: Financial ratios of the datasets

	Turkish banks' data
1	*Interest expenses/Average profitable assets*
2	*Interest expenses/Average non-profitable assets*
3	*(Share holders' Equity + Total income)/(Deposits + Non-deposit funds)*
4	*Interest income/Interest expenses*
5	*(Share holders' Equity + Total income)/Total assets*
6	*(Share holders' Equity + Total income)/(Total assets + Contingencies & Commitments)*
7	*Networking Capital/Total assets*
8	*(Salary and Employees' benefits + Reserve for retirement)/No. of personnel*
9	*Liquid Assets/(Deposits + non-deposit funds)*
10	Interest Expenses/Total Expenses
11	liquid assets/total assets
12	*Standard Capital ratio*
	Spanish banks' data
1	*Current assets/total assets*
2	*Current assets-cash/total assets*
3	*Current assets/loans*
4	*Reserves/loans*
5	*Net income/total assets*
6	*Net income/total equity capital*
7	*Net income/loans*
8	*Cost of sales/sales*
9	*Cash flow/loans*
	UK banks' data
1	*Sales*
2	*Profit before tax/capital employed (%)*
3	*Funds flow/total liabilities*
4	*(Current liabilities + long-term debit)/total assets*
5	*Current liabilities/ Total assets*
6	*Current assets/ Current liabilities*
7	*Current assets – stock / Current liabilities*
8	*Current assets – current liabilities/total assets*
9	*LAG (Number of days between account year end and the date of annual report*
10	*Age*

Sensitivity measures the proportion of the true positives (TP) correctly identified by a classifier.

$$\text{Sensitivity} = TP/ (TP+ FN)$$

Specificity measures the proportion of the true negatives (TN) correctly identified by a classifier.

$$\text{Specificity} = TN/ (TN +FP)$$

Accuracy measures the proportion of true positives and true negatives correctly identified.

$$\text{Accuracy} = (TP+TN)/ (TP+TN+FP+FN)$$

where TP, TN, FP and FN respectively stand for true positive, true negative, false positive and false negative.

In the case of Turkish dataset, it is observed that PCA-TAWNN yielded 100% accuracy, while PCNN-WFS-LTF [38] and TAWNN [47] also yielded 100% accuracy as presented in Table 2. Further, in the case of Spanish data (see Table 3), PCA-TAWNN yielded 100% accuracy, whereas PC-TANN [38] yielded an accuracy of 97.5% with an AUC of 8475. Thus, PCA-TAWNN achieved the highest accuracy possible, which could not be obtained by any other classifier so far in literature. In the case of UK data (see Table 4) it is observed that the PCA-TAWNN yielded an accuracy of 89.98% with 95.5% sensitivity and AUC of 8691, which is the best obtained so far. But, SVWNN [38] reported an accuracy of 81.67% with AUC of 7900.

Table 2: Average results of Turkish Banks dataset

Classifier	Acc*	Sens*	Spec*	AUC
MLP [34]	81.67	66.61	90.2	7840.5
TANN [38]	92.5	96.8	93.5	9515
PCA-TANN [38]	97.5	96.8	100	9840
PCNN-WFS-LTF [38]	100	100	100	10000
FRBC [43]	97.5	96.67	100	9833.5
SVM [44]	92.5	86.67	95	9041.5
WNN [47]	95	100	95	9750
DEWNN [47]	95	100	95	9750
TAWNN [47]	100	100	100	10000
SVWNN [44]	95	100	95	9750
KPCNN [45]	92.5	93.75	92.17	9317
PCA-TAWNN (Proposed)	**100**	**100**	**100**	**10000**

Acc*=Accuracy, Sens*=Sensitivity, Spec*=Specificity

Table 3: Average results of Spanish Banks

Classifier	Acc*	Sens*	Spec*	AUC
MLP[34]	81.67	66.61	90.2	7840.5
TANN[38]	91.6	98.5	81.5	9000
PCA-TANN[38]	97.5	97.5	72	8475
PCA-BPNN[38]	84.1	75.4	91.5	8345
Linear RBF[34]	75	51.71	90.17	7094
Orthogonal RBF[34]	40.83	97.5	7.3	5240
RSES[34]	92.5	87.5	97.5	9250
TreeNet[34]	77.96	86.55	93	8977.5
ANFIS [34]	63.34	44.45	79	6172.5
FRBC [43]	96.67	96	100	9800
SVM [44]	88.33	85.83	95	9041.5
WNN [42]	86.67	89.16	81	8508
DEWNN [42]	89.99	91.66	93	9233
TAWNN [42]	88.33	79.66	90.5	8508
SVWNN [44]	90	95	85.17	9008.5
KPCNN [45]	91.67	94.17	92.17	9341
PCA-TAWNN (Proposed)	**100**	**100**	**100**	**10000**

Acc*=Accuracy, Sens*=Sensitivity, Spec*=Specificity

Table 4: Average results of UK Banks dataset

Classifier	Acc*	Sens*	Spec*	AUC
MLP [34]	70.00	73.33	67.17	7025
RBF [34]	71.66	71.66	67.66	6966
ANFIS [34]	75	75.167	78.501	7683.4
TANN [38]	78	87.5	68.33	7791.5
SVM [44]	61.67	90	26.67	5833.5
WNN [47]	78.33	76.33	74.17	7525
SVWNN [44]	81.67	78.83	79.17	7900
KPCNN [45]	80	80.25	75.83	7916.5
PCA-TAWNN (Proposed)	**89.98**	**95.5**	**78.32**	**8691**

Acc*=Accuracy, Sens*=Sensitivity, Spec*=Specificity

Moreover, in the case of benchmark datasets, on WBC dataset, PCA-TAWNN yielded an accuracy of 79.86% with AUC of 7391 and on the Wine dataset it yielded an accuracy of 92.23%. These are however, not the best. The spectacular performance of the PCA-TAWNN on bankruptcy datasets is attributed to the dimensionality reduction capability of the PCA as well as the power and accuracy of the modified TAWNN.

6 Conclusions

In this paper we present a novel hybrid PCA-TAWNN for predicting bankruptcy in banks using PCA and modified TAWNN in tandem. Modified TAWNN comprises logistic or sigmoidal activation function at the output layer instead of the linear one unlike the original WNN and TAWNN. We analyzed three bank datasets *viz.*, Turkish, Spanish and UK and benchmark datasets Wine and WBC. First few principal components obtained from PCA are fed to modified TAWNN. It is observed from the empirical analysis that PCA-TAWNN performs best compared to other recent techniques. In the case of Spanish and Turkish banks datasets the proposed model yielded an astounding 100% percent accuracy, whereas in the case of UK banks dataset it yielded 89.98% accuracy with 95.5% sensitivity. The proposed model performed well on Wine and WBC as well. We conclude that the PCA-TAWNN hybrid can be used as a sound alternative to extant classification algorithms for bankruptcy prediction.

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