Comparison of Logistic Regression and Artificial Neural Network based Bankruptcy Prediction Models

Easwaran Iyer *, Vinod Kumar Murti**

Abstract

Logistic Regression is one of the popular techniques used for bankruptcy prediction and its popularity is attributed due to its robust nature in terms of data characteristics. Recent developments have explored Artificial Neural Networks for bankruptcy prediction. In this study, a paired sample of 174 cases of Indian listed manufacturing companies have been used for building bankruptcy prediction models based on Logistic Regression and Artificial Neural Networks. The time period of study was year 2000 through year 2009. The classification accuracies have been compared for built models and for hold-out sample of 44 paired cases. In analysis and hold-out samples, both the models have shown appreciable classification results, three years prior to bankruptcy. Thus, both the models can be used (by banks, SEBI etc.) for bankruptcy prediction in Indian Context; however, Artificial Neural Network has shown marginal supremacy over Logistic Regression.

Keywords: Bankruptcy, Logistic Regression, Artificial Neural Network, Classification Accuracy.

Introduction

Many researchers have built bankruptcy prediction models and tested in different countries. Among them, the most popular has been the model developed by Edward Altman (USA) in 1968 in which Multiple Discriminant Analysis was used. Next to Multiple Discriminant Analysis, Logistic Regression has been used extensively. Several other techniques like Probit Regression, Data Envelopment Technique, Time Series CUSUM Methodology, Cox Regression, Decision Tree Analysis, Simple Hazard Model, Black-Scholes Option-Pricing Model, Simple Fuzzy Logic, Artificial Neural Networks and Genetic Programmed Decision Trees were also used for exploring better discriminating models for bankruptcy prediction. We have found that very few researchers have conducted researches with Indian data. Moreover, most of the researches have been around Altman's model (1968) with Multiple Discriminant Analysis. There is a distinct gap between the researches done abroad and researches done in India with regard to application of discriminating techniques.

In this study, we compared one of the most popular techniques used for bankruptcy prediction, that is *Logistic Regression*, with a comparatively newer one that is *Artificial Neural Network* with Indian data. The independent variables were considered the same as those considered by Ohlson (1980) due to their worldwide acceptability. To the best of our knowledge, this is the first of its kind, which compares both techniques with Indian Data for bankruptcy prediction. We present a quick relevant *Literature Review* under section 2 followed by *Data and Methodology* under section 3 followed by *Analysis and Results* under section 4 followed by *Conclusions* under section 5 and *References* are mentioned at last under section 6.

Literature Review

In the paper published by Ohlson (1980), he had mentioned two unpublished papers by White and Turnbull (1975a; 1975b) and by Santomero and Vinso (1977) which were the first studies that had logically and systematically developed probabilistic estimate of failure. Ohlson had also used the methodology of maximum likelihood so called logit model or logistic regression. He had used 58 bankrupt and 2058 non-bankrupt companies in his sample

* Director and Dean – Commerce and Management, Jain University, Bangalore, Karnataka, India. E-mail: easwaran.iyer@jainuniversity.ac.in

** Academic Head - i Nurture Education Solutions Private Limited, Bangalore & Faculty at Commerce and Management, Jain University, Bangalore, Karnataka, India. E-mail: vinod@inurture.co.in

pertaining to the time period of 7 years from 1970 to 1976. He believed that if financial statements are disclosed after the declaration or filling of bankruptcy, there are very high chances that the firm might back-cast the results. Under these circumstances, the financial results were bound to reflect bias and did not reflect true position. For the sake of not including such companies in his study, Ohlson had referred to Accountant's Reports. Ohlson had considered only three reporting periods (years) prior to bankruptcy. He had further mentioned that many important problems pertaining to the development of data for bankrupt firms had not been addressed in the literature. Ohlson had mentioned the strict assumptions of Multiple Discriminant Analysis which demands mainly i) equality of variance-covariance matrices of the predictors among failed and non-failed groups and ii) normally distributed predictors. He had further mentioned that under many circumstances, researcher is interested towards more traditional econometric analysis and test variables for statistical significance where the above-cited assumptions create limitations. Furthermore, he had mentioned that use of dummy predictors displays departure from these assumptions. Ohlson formed the opinion that discriminant scores developed by Multiple Discriminant Analysis have little intuitive interpretation. Ohlson had further stated that the matching of sample on the basis of size and industry is somewhat arbitrary. Logit analysis, on the other hand, is free from assumptions regarding prior probabilities and distributional properties of predictors. He had cited this as a major advantage of using logit analysis. With regard to statistical significance, Ohlson had stated that this could be obtained through asymptotic (large sample) theory. He had used the following predictors: *i) Size: log (total assets/GNP price index). The index assumed a base value of 100 for 1968. ii) Total Liabilities/Total Assets. iii) Working Capital/Total Assets. iv) Current Liabilities/Current Assets. v) OENEG; One if total liabilities exceed total assets, otherwise zero. vi) Net Income/Total Assets. vii) Funds from Operations/Total Liabilities. viii) INTWO; One if net income was negative for the last two years, otherwise zero. And ix) CHIN;* $(NI_t - NI_{t-1})/(Mode\ NI_t - Mode\ NI_{t-1})$. Ohlson had built three models for one year prior to bankruptcy, two years prior to bankruptcy and three years prior to bankruptcy and found 96.12, 95.55 and 92.84 percent correctly classified. Finally, Ohlson had concluded that i) the timing issue with regard to declaration of bankruptcy and disclosure of financial statements were important and should not be ignored and ii) additional predictors, particularly market related predictors should be explored for improving the predictions.

Luther (1994) had compared ANN with Logistic Regression with the help of 104 sample size of US companies. The study period was 1984 through 1989. The neural network was trained using the Genetic Algorithm technique, which iterates towards the optimum solution by looking only at the value of the objective function and not getting trapped in the local minima. Thirteen predictors were selected for model building by ANN and LR. The study concluded that ANN model had significantly higher prediction accuracy than the Logit Model in both the training samples and the hold-out samples at almost all cut-off points. Luther mentioned that that the prediction accuracy was less sensitive to changes in the cut-off point in the model, thus making ANN more robust technique than Logit.

Zhang, Hu, Patuwo, and Indro (1999) had studied matched sample of 220 US firms 1980 through 1991 and explained the link between ANN and traditional Bayesian classification theory. They found that ANN models were significantly better than Logistic Regression models in prediction as well as classification rate estimation. They reported that ANN was robust to sampling variations in overall classification performance.

Javanmard and Saleh (2009) had used a sample of 80 companies and compared Multiple Discriminant Analysis and Artificial Neural Network. They mentioned that the ANN has been used to solve many financial problems including forecasting financial distress and many researchers using ANN to forecast financial distress have come to the conclusion that the accuracy of ANN is much more effective than the traditional statistical methods. They quoted Cerano-Sinka's work on comparison of MDA & ANN where Cerano-Sinka got forecasting accuracy as 86% and 94% respectively. Javanmard and Saleh had also reported superiority of ANN over MDA in their study.

Lin (2009) had compared MDA, Logit, Probit and ANN models for bankruptcy prediction in Taiwan. He had studied Taiwan public industrial firms for the period 1998-2005. Final models were validated through out-of-the sample data. Lin found Probit models as the best among all in terms of classification accuracies and stability. Lin had mentioned that if the data does not satisfy the assumptions of statistical approach, then the ANN approach would demonstrate its advantage and achieve higher prediction accuracy.

Wang and Campbell (2010) had studied the application of Ohlson's model on Chinese publicly traded companies during the period 1998-2008. They had mentioned that the Chinese economy was significantly affected by the 2008-09 Global Financial Crisis due to the export oriented nature of the economy. They had reported from the reference of Thurston (2009) that 28 percent increase in overall bankruptcy filling and 29 percent increase in commercial bankruptcy filling in February, 2009 were witnessed vis-à-vis last year. Chinese stock exchange started in 1990; but, the first delisting took place in the year 2001 with the delisting of Shanghai Narcissus Electric Appliances Co., Ltd. In 2006, Chinese GAAP for reporting financial statements was changed to IFRS. Wang and Campbell had collected a sample of 1336 companies from manufacturing and non-manufacturing industry sectors. The Ohlson model gave overall prediction of 95 percent; but, prediction of non-failed companies was very poor.

Data and Methodology

We have explained design of hypothesis, data preparation, brief outline of discriminating techniques used in this study viz., Logistic Regression and Artificial Neural Network and tools and techniques used for analysing classification results in the following section.

Design of Hypothesis

For comparing and judging the best displayed classification accuracies by the models based on Artificial Neural Network and Logistic Regression, the following hypothesis was designed and tested later on:

H_o*: *There is* **no** *statistically significant difference between the Classification Accuracies for Bankruptcy Predictions displayed by the models based on Artificial Neural Network and Logistic Regression.

***H_a*: There is** *statistically significant difference between the Classification Accuracies for Bankruptcy Predictions displayed by the models based on Artificial Neural Network and Logistic Regression.*

The Proposed Level of significance was 5%.

Data Preparation

This section explains the sample preparation, validation sample, and independent and dependent variables.

Sample Preparation

For building models for bankruptcy prediction, pairs of bankrupt and non-bankrupt companies were needed. The names of bankrupt companies were taken from the official web site of BIFR (Board of Industrial and Financial Reconstruction). A ten year period was studied in this study. In this ten-year time period, total 2678 companies had filed for bankruptcy. Availability of financial data was one of the major constraints. Out of 2678, only 1152 companies had their presence in **Capitaline** data source. Further, the study was pertaining to only manufacturing and listed companies only, we could find only 827 bankrupt manufacturing companies available in **Capitaline** data source. Out of 827, only 245 bankrupt companies had their financial data available for the past five years prior to bankruptcy. Further, 50 bankrupt companies were found repetitive in the list available on site. These 50 companies were deleted from 245 bankrupt companies. As a practice followed by previous researchers to not select smaller companies in their studies, which seems logical as small companies are more prone to financial distress due to variety of reasons, we also deleted 58 small companies whose Total Assets for the third year prior to bankruptcy was less than INR 30 Crores. We made third year as the reference year prior to bankruptcy for pairing purpose and for the purpose of comparison of Total Assets. This is because that the year bankruptcy was filed is bound to show lowest Total Assets. Third year prior to bankruptcy is supposed to show comparable financial health (of bankrupt and non-bankrupt companies) in terms of Total Assets. On the same note comparatively too big should also not be included in the sample. For the same reason, 2 bankrupt companies were also deleted. Finally, we left with 135 bankrupt companies belonging to only manufacturing and listed category and filed for bankruptcy. These 135 bankrupt companies were attempted for pairing. For meaningful pairing, the following considerations were taken into account. The prospective pair of a bankrupt company should be i) belonging to manufacturing industry ii) listed in any of the stock exchange so that Market Capitalisation can be computed iii) belonging to the same or nearly same industry classification (of bankrupt company), iv) of almost same size with a plus minus variation of 30% v) free from bankruptcy filing vi) financially healthy and vii) having financial data of last five years prior to bankruptcy. As a result of the above mentioned criteria, we could match or pair only 109 bankrupt companies with non-bankrupt companies. Thus, the sample size became of 218 cases. Six data sets were prepared pertaining to year of bankruptcy, t0 through fifth year prior to bankruptcy, t5.

Selection of Validation Sample

We randomly selected 20% of 218 cases which resulted into 22 paired cases totalling 44 cases for validation purpose. These 44 cases (hold-out sample) were not used for building the model. The build models were validated by this holdout sample. The model building data sets were having 174 cases (87 cases for bankrupt nomenclature as group_1 and 87 cases for non-bankrupt cases nomenclature as group_0 in this study). Six data sets were prepared for validation pertaining to year of bankruptcy, t0 through fifth year prior to bankruptcy, t5.

Independent and Dependent Variables

We have mentioned in the introduction (section 1) that we considered the *independent variables* selected by Ohlson (1980) due to their worldwide acceptability. These are mentioned at the beginning of section 2 where we have mentioned the notable paper of Ohlson (1980). Dependent variables were 0 and 1 for non-bankrupt and bankrupt outcome.

Software Used

We used SPSS Version 20 for model building, validation, building Receiver Operating Characteristic Curves and applying One Sample Kolmogorov Smirnov and Paired Sample t-tests.

Classification Techniques

Two classification techniques were applied on 6 data sets and classification results were compared for judging the efficacy of discriminant techniques. Both the techniques are explained in short as below.

Logistic Regression

Logistic Regression is a specialized form of regression that is formulated to predict and explain (two-group) categorical variable rather than a metric dependent measure. The form of the logistic regression variate is similar to the variate in multiple regressions. The variate represents a single multivariate relationship with regression-like coefficients indicating the relative impact of each predictor variable. Logistic Regression differs from multiple regression, however, in being specifically designed to predict the probability of an event occurring that is the probability of an observation being in the group coded 1. Because the binary dependent variable has only the values 0 and 1, the predicted value (probability) must be bounded to fall within the same range. To define a relationship bounded by 0 and 1, logistic regression uses the *logistic curve* to represent the relationship between independent and dependent variables.

This *logistic curve* ensures i) the predicted values are always between 0 and 1 and ii) the predicted values correspond to the probability of Y (Dependent variable) being 1, in our case, bankruptcy. The logistic regression is first performed with a transformed value of Y, called the *logit function* as shown below:

$$\text{Logit }(Y) = \text{In(odds)} = a + k_1x_2 + k_2x_2 + \cdots + k_nx_n \qquad (2.1)$$

Where *odds* refer to the odds of Y being equal to 1.

$$\text{Odds} = \frac{\text{Probability}}{1 - \text{Probability}} \qquad (2.2)$$

Odds are defined mathematically as:

$$\text{Probability} = \frac{\text{Odds}}{1 + \text{Odds}} \qquad (2.3)$$

Odds can be converted into probabilities by the following expression:

The right hand side of Equation (2.3) does not guarantee values between 0 and 1. Hence, exponent of each side is taken as shown below:

$$e^{\text{In(odds)}} = \text{odds} = e^{(a + k1x1 + k2x2 + \cdots + knxn)} \qquad (2.4)$$

Now dividing both sides of Equation (2.4) by (1+odds) results into:

$$\frac{\text{Odds}}{(1 + \text{odds})} = \frac{e^{(a + k_1x_1 + k_2x_2 + \cdots + k_nx_n)}}{(1 + e^{(a + k_1x_1 + k_2x_2 + \cdots + k_nx_n)})} \qquad (2.5)$$

The right hand side of Equation (2.3) is equitable to right hand side of Equation (2.5). Hence, the equation looks like:

$$\text{Probability} = \frac{e^{(a + k_1x_1 + k_2x_2 + \cdots + k_nx_n)}}{(1 + e^{(a + k_1x_1 + k_2x_2 + \cdots + k_nx_n)})} \qquad (2.6)$$

The Equation (2.6) yields p, probability of belonging to a group (Y=1, bankrupt) rather than the log of the *odds* of the same. SPSS version 20 has the capability of computing the coefficients k_n for the regression shown in Equation (2.1). Thus, the computation of probabilities of belonging to Group_1 is done. The Equation (2.6) can only yield values that are between 0 and 1.

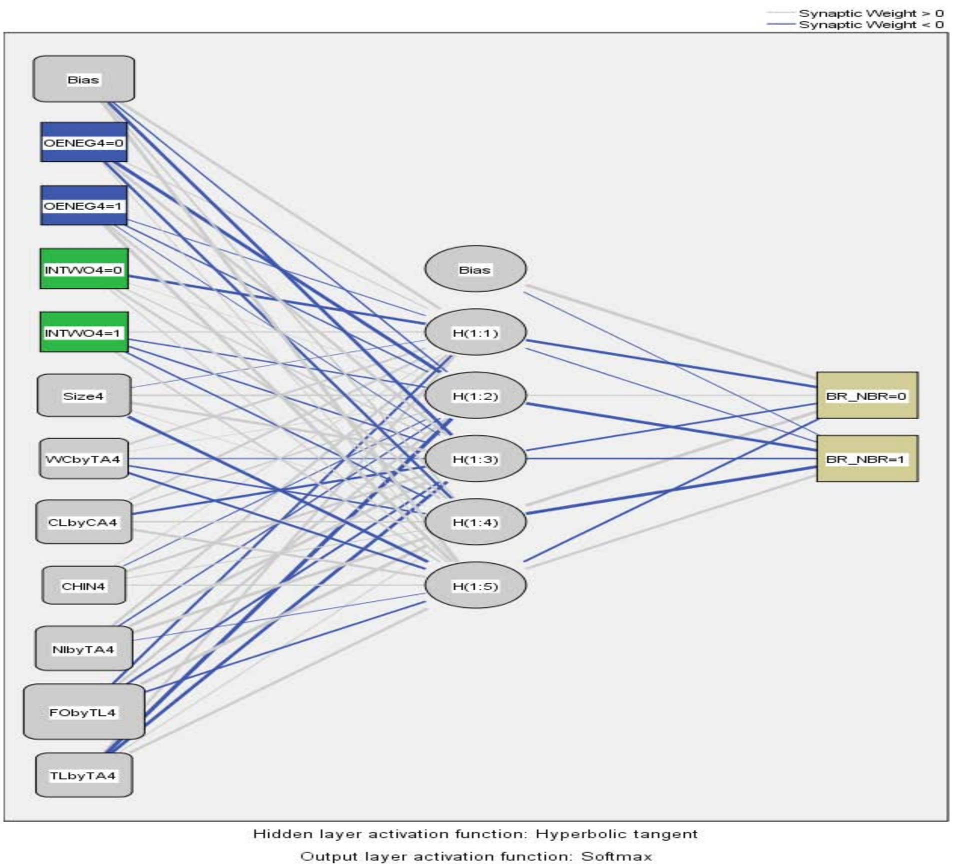
Artificial Neural Network

A neural network's ability to perform computation is based on the hope that we can produce some of the flexibility and power of the human brain by artificial means. Network computation is performed by a dense mesh of computing nodes and connections. They operate collectively and simultaneously on most or all data and inputs. The basic processing elements of neural networks are called artificial neurons, or simply neurons. Neurons perform as summing and nonlinear mapping junctions. They are often organized in layers, and feedback connections both within the layer and toward adjacent layers are allowed. Each connection strength is expressed by a numerical value called a *weight*, which can be modified. A typical Neural Network diagram (used for data set for year t2 as an example) is shown in Figure 1.

As shown in the Figure 1, there is one input layer (left most), one hidden layer (middle one) and one output layer (right most). Within input layer, there are 5 nodes equal to numbers of predictors. Output layer has 2 nodes as levels of dependent variable (bankrupt 1 and non-bankrupt 0). The numbers of nodes, 2 in hidden layer can be adjusted.

The network specifications followed in building the models were: (i) 70:30 ratio was set for training and testing network (ii) Hyperbolic Tangent function was used as activation function for hidden layer (iii) Softmax

Figure 1. Artificial Neural Network Diagram



Source: SPSS Output.

function was used as activation function for output layer (iv) Range of nodes in hidden layers was set as 1 to 50 (v) Batch Training was used for training network (vi) Scaled Conjugate Method was used as Optimization algorithm (vii) Initial Lambda was set as 0.0000005 (viii) Initial Sigma was set as 0.00005 (ix) Interval centre was set as 0.00 (x) Interval offset was set as ± 0.50 (xi) Minimum Relative change in Training Error was set as 0.0001 (xii) Minimum Relative change in Training Error Ratio was set as 0.001(xiii) Maximum Training Time was set as 15 minutes and (xiv) Maximum steps without a decrease in error was set as 1.

Hyperbolic Tangent function has the following form:

$$Y(c) = \tan h\,(c) = \frac{(e^{c} - e^{-c})}{(e^{c} + e^{-c})} \tag{2.7}$$

Where, c is the input from previous nodes. Y(c) takes real-value arguments and transforms them to the range (– 1, +1).

Softmax function has the following form:

$$Y(c) = \frac{1}{1 + e^{-c}} \tag{2.8}$$

Y(c) takes real-value arguments and transforms them to the range (0, +1).

Tools for Analysing Classification Results

Empirical analysis of classification results which was vertical (across the years) and horizontal (across the discriminating schemes) was the preliminary analysis tool. Comparison of classification results produced by models was done with the help of *ROC curves*. *Paired Sample t-test* was used for hypothesis testing.

Analysis and Results

The 6 data sets pertaining to year of bankruptcy (t0), one year prior to bankruptcy (t1), two years prior to bankruptcy (t2), three years prior to bankruptcy (t3), four years prior to bankruptcy (t4) and five years prior to bankruptcy (t5) were run through Logistic Regression (LR) and Artificial Neural Network (ANN) by SPSS. The classification accuracies of models and validated results have been discussed in the following section.

Models Overall Classification Accuracies

The following Table 1 shows overall classification accuracies in percentages displayed by Artificial Neural Network (ANN) and Logistic Regression (LR). The last column shows the difference between overall classification accuracies displayed by each models.

Table 1: Overall Classifications through ANN and LR Models

Years	*Overall ANN Model*	*Overall LR Model*	*Difference: ANN-LR*
T0	91.10	89.70	+1.40
T1	84.40	83.90	+0.50
T2	81.50	77.59	+3.91
T3	75.20	73.56	+1.64
T4	75.00	70.12	+4.88
T5	70.20	69.54	+0.66

Source: *SPSS Output.*

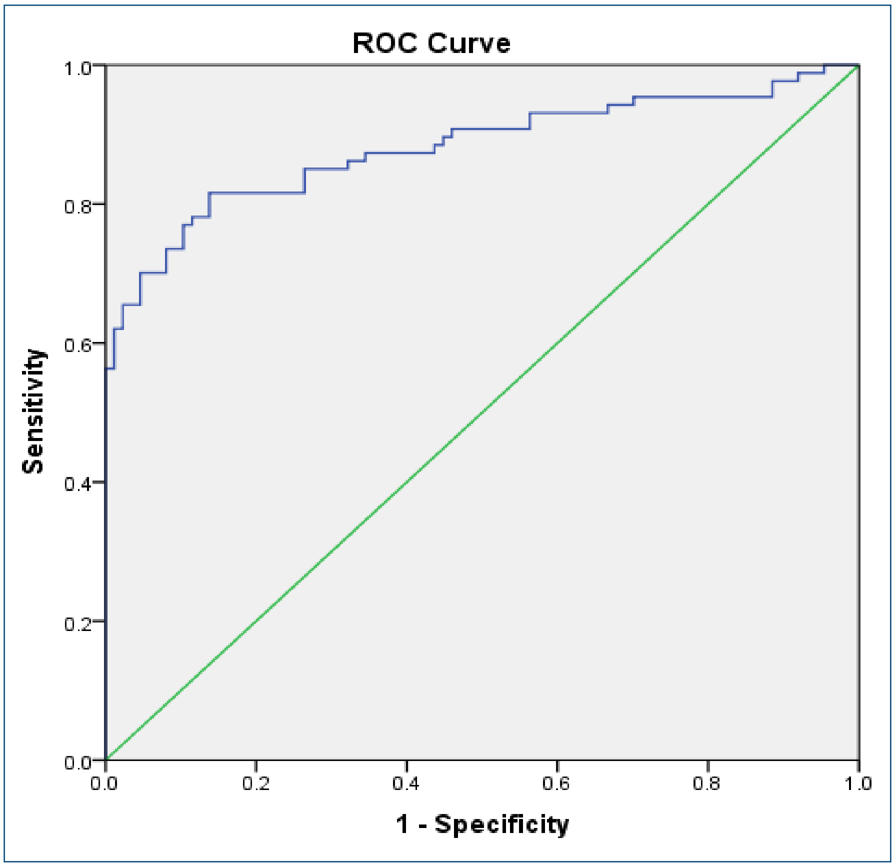
Both the models showed the highest classification accuracy for the year t0 and the lowest for the year t5. This was because of diminishing discriminating capability

Table 2: Predictors Prediction Capability

Years	*Numbers of Poor Predictors*	*Poor Predictor's p-value of F statistics/Chi-square statistics [>0.05]*
T0	2	CL/CA [0.733], CHIN [0.101]
T1	1	CL/CA [0.623]
T2	3	WC/TA [0.346], CL/CA [0.271], CHIN [0.187]
T3	4	SIZE [0.095], WC/TA [0.504], CL/CA [0.883] & ***OENEG [0.202]***
T4	4	SIZE [0.223], WC/TA [0.975], CL/CA [0.485] & ***OENEG [0.469]***
T5	6	SIZE [0.272], WC/TA [0.892], CL/CA [0.289], CHIN [0.136], FO/TL [0.097] & ***OENEG [0.35]***

Source: *SPSS Output.*

Figure 2. Receiver Operating Characteristic Curve



Source: SPSS Output.

of predictors across the years. The year of bankruptcy, t0 had maximum discriminating capability possessed by predictors. This was obvious as bankrupt companies were financially strained at the year of filing for bankruptcy whereas their counter parts (in the analysis, non-bankrupt and healthy companies) were not experiencing any financial strain as captured by predictors or financial ratios. However, 5 years prior to year of bankruptcy, both categories of bankrupt and non-bankrupt did not have *so* differentiable predictors or, in other terms, both the categories were almost the same. Table 2 shows poor prediction capability of predictors judged through F-test for continuous predictors and through Chi-square test for categorical predictors at 5% level of significance.

The comparison of overall classification accuracies clearly favoured the supremacy of ANN over LR. All years showed marginally higher classification accuracies by ANN models. In the year's t2 and t4, the differences were impressive in the tune of 3.91 and 4.88 respectively. The differences were found significant at 5% level of significance with p-value as 0.032 associated with Paired Sample t-test. Prior to Paired Sample t-test, the classification accuracies displayed by ANN and LR were tested by One Sample Kolmogorov Smirnov test and p-values were found as 0.939 and 0.987 respectively. Thus, necessary condition for applying Paired Sample t-test was met.

The above results were crosschecked by the areas under Receiver Operating Characteristic Curves (ROC) captured by ANN and LR. ROC curves are plotted against *(1-specificity)* on X-axis and *sensitivity* on Y-axis for a range of cut-offs. Sensitivity is the probability of classifying a case wrongly when the case belongs to category 1. This is termed as Type I error in the domain of terminologies used for explaining classification results. Similarly, specificity is the probability of classifying a case wrongly when the case belongs to category 0. This is termed as Type II error. ROC curves are used for comparing different discriminating schemes. The closer the ROC curve towards left top corner, the better the

Table 3: Area under Receiver Operating Characteristic Curves through ANN and LR Models

Years	*Area under ROC Curve ANN Model*	*Area under ROC Curve LR Model*	*Difference: ANN-LR*
T0	95.40	95.40	0.00
T1	91.60	91.30	+0.30
T2	89.30	86.30	+3.00
T3	81.40	80.60	+0.80
T4	81.20	80.80	+0.40
T5	74.60	75.70	-1.10

Source: SPSS Output.

curve is. Judging closeness of *two* ROC curves towards left top corner is a subjective matter which is resolved by the term 'area under ROC curve'. Area under ROC curve is an indication of efficiency of classification scheme. Thus, the higher the area under ROC curve, the better is the discriminating scheme. ROC curves are generated for ANN by SPSS V 20; however, for LR, these are not default output. ROC curves for LR were generated by separate commands through SPSS V 20.

A typical ROC Curve has been shown in Figure 2.

The Table 3 shows the areas under Receiver Operating Characteristic Curves captured by ANN and LR across the years. The last column shows the differences in areas under ROC curves captured by ANN and LR models.

As evident from the above table, areas under ROC curves were marginally higher in case of ANN models across the years. Besides, year t3 which showed higher area captured by ANN model by 3.00 percent, rest of the years were marginally higher in case of ANN models. The differences were found not significant at 5% level of significance with p-value as 0.352 associated with Paired Sample t-test. Prior to Paired Sample t-test, the areas under ROC curves captured by ANN and LR were tested by One Sample Kolmogorov Smirnov test and p-values were found as 0.964 and 0.943 respectively. Thus necessary condition for applying Paired Sample t-test was met.

The Overall classification results and Areas under ROC curves captured by ANN and LR models were better for ANN models; however, the final verdict can be framed only after analyzing Validation results which are discussed below.

Validated Overall Classification Accuracies

We took out 44 cases (22 bankrupts and 22 non-bankrupts) out of initial paired samples of 218 cases for each of six years for validation purpose. These 44 cases were not used for model building. The models were first saved in ***xml*** files and then later applied by *Scoring Wizard* commands available under *Utilities* in SPSS V 20 software.

Table 4 shows the Validated Overall classification accuracies displayed by ANN and LR. The last column shows the difference between overall validated results displayed by ANN and LR.

Table 4: Overall Validated Classifications through ANN and LR Model

Years	*Overall* **validation** *by ANN Model*	*Overall* **validation** *by LR Model*	*Difference: ANN – LR*
T0	100.00	97.73	+2.27
T1	79.56	81.82	-2.26
T2	79.56	81.82	-2.26
T3	72.73	72.73	0.00
T4	63.64	52.30	+11.34
T5	63.64	59.10	+4.54

Source: SPSS Output.

Validated results were the same for year t3, higher by LR models in years t1 and t2 both by 2.26 percent and higher by ANN models for years t0, t4 and t5. The lead taken by ANN model over LR model for year t4 was spectacular in the tune of 11.34 percent. These mix results could not show supremacy of any model over another. Paired Sample t-test showed p-value as 0.331 which was not significant at 5% level of significance, thus confirming the statistically same performance by both the models. Prior to Paired Sample t-test, the validation results by ANN and LR were tested by One Sample Kolmogorov Smirnov test and p-values were found as 0.866 and 0.993 respectively. Thus, necessary condition for applying Paired Sample t-test was met.

As a commonly accepted/practiced rule of thumb (gathered through extensive literature review) of considering a classification accuracy more than 70% as good classification accuracy depicts that both ANN and LR models could display good validated results till year t3 (three years prior to bankruptcy).

Conclusions

In this work, we compared the classification accuracies of bankruptcy prediction models based on Logistic Regression and Artificial Neural Networks. Based on *Overall Classification results*, *areas under Receiver Operating Characteristic Curves* and *Validated Overall Classification results*, models based on Artificial Neural Network were found marginally better. Our findings were in line with the findings of Luther (1994), Zhang (1999) and Lin (2009). However, stability of ANN remains an issue which needs attention by technique developers. Altman had mentioned in his paper pertaining to study with Italian data that the behavior of the network became at times unexplainable and unacceptable. Altman had further mentioned in the same paper that ANN had shown enough promising features to provide an incentive for better implementation techniques and more creative testing.

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