DOCTORAL ABSTRACT

Comparative Credit Risk Assessment Structures in Indian Banking Industry

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ABSTRACT

Bankruptcy is a state of insolvency wherein the company or the person is not able to repay the creditors the debt amount. The purpose of this research is to develop and compare the performance of bankruptcy prediction models using multiple discriminant analysis, logistic regression and neural network for listed companies in India. These bankruptcy prediction models were tested, over the three years prior to bankruptcy using financial ratios. The sample consists of 72 bankrupt and 72 non-bankrupt companies over the period 1991-2016. The results indicate that as compared to multiple discriminant analysis and logistic regression, neural network has the highest classification accuracy for all the three years prior to bankruptcy.

Keywords: Bankruptcy prediction, Multiple discriminant analysis, Logistic regression, Neural network

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INTRODUCTION

The Indian Insolvency and Bankruptcy Code 2016 describes Bankruptcy as "a legal status usually imposed by court, on a firm or an individual who is unable to meet his debt obligations. Upon successful completion of the bankruptcy proceedings, the debtor is relieved of the debt obligations incurred prior to filing for bankruptcy."[1] However, the Insolvency is described in the code as "a situation where individuals or organizations are unable to meet their financial obligations."[2] This code has created an institutional mechanism and insolvency resolution process for business operated by companies, individual or any other entities, either by coming up with a viable survival mechanism or by ensuring their prompt liquidation.

Bankruptcy is defined as the inability of the company to continue its current operations due to high debt obligations (Pongsatat et.al., 2004). Typically, bankruptcy occurs "when either (i) the firm's operating cash flow is insufficient to meet current obligations which means, the inability to service its debts or (ii) when the firm's net worth is negative that means, the value of the assets is less than the value of its external liabilities" (Knox et. al., 2008).

Bankruptcy is a position where a company is not capable of repaying its liabilities. There can be numerous other reasons for bankruptcy of a company such as assets falling short of liabilities, scarcity of cash, inefficient management or even declining trend in sales. Predicting bankruptcy turns out to be very crucial in taking preventive measures regarding liquidity, solvency and profitability position of the company. Predicting bankruptcy involves collecting relevant financial information of the firm, place it in a credible model to verify and predict the future bankruptcy to take required precautions well in advance.

Bankruptcy prediction is among the most well researched topics in the finance and strategic management literature (Polemis & Gounopoulos, 2012). The early researchers (Ramser & Foster, 1931; Fitzpatrick, 1932; Winakor & smith, 1935) focused on the comparison of the values of financial ratios in bankrupt and non-bankrupt companies and concluded that the ratios of the bankrupt companies were poor (Ugurlu & Aksoy, 2006). Altman (1968) used multivariate discriminant analysis for prediction of corporate bankruptcy. In the 1970s, multiple discriminant analysis was the primary method for prediction of corporate bankruptcy. During the 1980s, use of logistic regression analysis method was emphasized, (Virag & Kristof, 2005). However, Ohlson (1980) applied logistic regression analysis for the first time for prediction of bankruptcy. In recent years, a number of researchers have begun to apply the neural network approach to the prediction of bankruptcy as they have produced promising results in prediction of bankruptcy (Ugurlu & Aksoy, 2006). Odom and Sharda (1990) were first to use Neural networks for bankruptcy prediction.

The objective of this study is to develop a bankruptcy prediction model by taking data of Indian listed companies using multiple discriminant analysis, logistic regression and neural network and compare the performance of the three models.

LITERATURE REVIEW

Vasantha, Dhanraj & Thiayalnayaki (2013) studied selected Indian airline companies. The sample of the study consisted of Kingfisher airlines, Spice Jet airways and Jet airways. Authors also studied financial and operational performance of these companies. The financial soundness of these airline companies was evaluated using Altman's original Z score, Revised Z score model and revised four models. The study also compared the above-mentioned models to suggest strategies for making the right moves.

Muthukumar & Sekar (2014) used Altman Z score and Springate models to study the financial health of automobile sector in India. The study was conducted for the period of 2003 to 2012, to check how the global financial crisis affected the automobile sector, which indicates the economic growth of the country. The authors took scores of all companies to calculate an average to create a benchmark for comparison. It has been concluded that none of the companies are in a distressed state.

There have been various methods developed and used across the industries. Some of the more common methods are the Altman Z score and the Merton's distance to default model. Each model has its own limitations and financial institutions are always on the look-out for finding the best method to evaluate credit worthiness.

There have been many related studies in the past which assessed the efficiency of the prediction models. Attempts to find out the best prediction model have been umpteen but none of them have been very successful. Moreover, most of these studies have been on a global scale and concentrate more on firms that are huge multinationals. The purpose of our research is to study the suitability of major bankruptcy prediction models by applying them to companies in the Indian manufacturing sector that have been declared sick and by doing so find out which models are more suitable for firms in this sector.

Most studies conducted in the past, lacked validity and were deficient in a number of ways. A review of statistical and theoretic prediction models was presented by Scott (1981), but it was very limited in coverage and can be considered out of date in the current context. Zavgren (1983) describes only the statistical models without any mention of the theoretical models. The first ever study was by Altman (1984), which was done taking ten countries and is an interesting study but limits itself to only one type of statistical model. However, Jones (1987) tried to give a comprehensive view of all the prediction models and focused on research done in the corporate

[1] *https://www.quora.com/What-is-the-difference-between-insolvency-bankruptcy-and-liquidation.*
[2] *http://finmin.nic.in/reports/BLRCReportVol1_04112015.pdf.*

bankruptcy prediction area, but did not discuss theoretical methods or models.

Zhang et. al., (1999), tries to understand the role of neural networks to predict bankruptcy. They have also discussed the empirical applications of the networks for predicting bankruptcy but have left out all other types of models that are generally used by various firms.

From the review of various studies, it can be concluded that the business failure research can be categorized into following three broad statistical techniques:

1. Accounting Based Bankruptcy Predicting Model
2. Market Based Bankruptcy Predicting Model
3. Artificial Intelligence Based Bankruptcy Predicting Model

The above three techniques have been frequently applied in numerous studies for predicting bankruptcy. A review of these studies is presented in detail as follows.

Accounting Based Bankruptcy Predicting Model

This takes into consideration firm's previous performance as a base for predicting its future likelihood of survival (Xu and Zhang, 2008). Several studies that include accounting variables for corporate bankruptcy prediction are Beaver (1966), Altman (1968), Ohlson (1980), Dichev (1998), Shumway (2001) etc.

Market Based Bankruptcy Predicting Model

This model uses the information derived from the market, i.e., market prices. Since such information is inherently forward looking, market based approach depicts a firm's future performance considering market variables (Xu and Zhang, 2008). In the literature, this new methodology that uses market based variables for bankruptcy prediction usually follows Black and Sholes (1973) and Merton (1974) option pricing theory that expresses probability of bankruptcy occurring, this in turn depends on the volatility between the market value of the assets and the strike price (value of debt obligations). The critical level where firm will default is that when the worth of the firm's assets moves down below a certain level (i.e., debt obligations). However, these theories provide no incremental information when the market is in semi-strong form (Hillegeist et. al., 2004). Several recent studies that have used market-based variables for predicting default probability of a firm include Crosbie and Bohn (2002), Brockman and Turtle (2003), Vassalou and Xing (2004), and Reisz and Perlich (2007).

Hillegeist et.al., (2004), compare the market based approach (i.e., Black Sholes and Merton) with some accounting based approaches (i.e., MDA and Logit) and conclude that the market-based approach provides significantly more information about the default probability of a firm vis-a-vis accounting-based approach. Contrary to Hillegeist, a study conducted by Reisz and Perlich (2007) examine default probability of 5,784 industrial firms by employing both market and accounting based approaches. This study provides that the accounting-based measures outperform Black-Sholes-Merton measure and recommends them for achieving an optimal default prediction.

Artificial Intelligence Based Bankruptcy Predicting Model

The technological advancement in informatics has evolved artificial intelligence techniques/methods that provided researchers to employ computer databases to estimate failure prediction (Charitou et.al., 2004). Artificial Intelligence (AI) methods that include decision tree, fuzzy set theory, genetic algorithm, support vector machine, data envelopment analysis, case-based reasoning, rough sets theory, and various types of neural networks such as PNN (Probabilistic Neural Networks), BPNN (Back Propagation Trained Neural Network), SOM (Self-Organizing Map), Cascor (Cascade Correlation Neural Network), and many more (see, for more on this, Min and Jeong, 2008).

Artificial intelligence technique has been applied in various countries such as Iran, Greece etc. Etemadi et.al., (2008) and has employed both MDA and Genetic Programming (GP) techniques for forecasting the default probability in Iranian firms. The study notes GP with a high accuracy of default prediction for Iranian firms. Moreover, Zanakisand Zopounidis (1997) employs a case study technique to distinguish between the financial variables of acquired and non-acquired Greek firms. The mixed results were found because of using similar financial ratios profiles between acquired and non-acquired firms. Furthermore, researchers have used different artificial intelligence techniques and propose alternative bankruptcy prediction model. Min and Jeong (2009) suggest a new binary classification technique for forecasting the default probability of firm by validating its prediction power through empirical analysis. Jo and Han (1996) employ both the discriminant technique and two artificial intelligence models (i.e, case-based forecasting and neural network) and suggest integrated approach for attaining high classification accuracy in predicting default characteristics of firms.

All the above three broadly categorized approaches (proposed by different researches) have essential advantages and limitations as well. Therefore, lacking standardized theory has led studies to employ different techniques according to their unique structure of corporate environment and country (Etemadi et.al., 2009).

Numerous researchers have compared the performance of different models of bankruptcy prediction. However, not much research has been conducted using the data of Indian companies.

Charitou, Neophytou and Charalambous (2004) developed bankruptcy prediction models for UK industrial firms using Neural Networks and Logistic Regression models. The results indicated that the neural network model achieved the highest overall classification rates for all three years prior to insolvency. Virang and Kristof (2005) conducted a comparative study of bankruptcy prediction models on the database of

Hungarian companies. They provided that bankruptcy models built using neural networks have higher classification accuracy than models based on MDA and logistic regression.

However, in case of some other studies the results were unsettled. Altman, Marco and Varetto (1994) applied neural network and MDA to large database of 1000 Italian firms for one year prior to their bankruptcy. The comparison yielded no decisive winner. Thus, based on international experience a comparative study is necessary to identify whether international trends can be applied to Indian firms' bankruptcy prediction as well.

METHODOLOGY AND DATA

The Sample and Variable Definition

For the present study, the bankrupt company is considered to be a company that is delisted from the stock market. The company that is delisted from Bombay Stock Exchange or National Stock Exchange and whose latest net worth and the net worth prior to the year of delisting is negative. And for the bankrupt companies, the year of bankruptcy will be the year in which its net worth became negative. For example: if a company is delisted in the year 2002 because its net worth has become negative in the year 1995, then the year 1995 has been considered as the year of bankruptcy. Financial institutions delisted companies merged with other companies and companies for which at least three years' full financial statements prior to the year of bankruptcy were not available are excluded from this research.

From 1991 with the start of economic liberalization in India, major structural changes took place in the Indian economy. Thus, the period considered for this study spans from 1991 to 2016. Application of the above stated definition of bankruptcy in this duration resulted in a sample of 72 companies as bankrupt. Similar to Altman's (1968) study's procedure, a twin company was chosen up that did not bankrupt from the same industry and approximately matched for asset size prior to the year of bankruptcy. This process has also been applied in majority of previous bankruptcy prediction studies. In order to develop bankruptcy models the companies are matched or made pairs so as to isolate key factors which distinguish otherwise similar firms (Morris, 1997). Thus, the total sample consists of 138 companies.

The bankrupt and non-bankrupt companies are randomly split to create distinct analysis and holdout samples. The analysis sample contains 50 bankrupt and 50 non-bankrupt companies and the holdout sample contains 22 bankrupt and 22 non-bankrupt companies.

Predictor Variable Selection

Similar to the previous studies that have used financial accounting ratios in their empirical studies of bankruptcy prediction, this study also employs financial ratios for development of bankruptcy prediction models. Previous studies revealed many significant predictions of bankruptcy

TABLE 1: EMPLOYED FINANCIAL RATIOS

Category	Variable Name	Variable Definition
Operating Cash Flow	CF/TA	Cash Flow from Operations/Total Assets
	CF/CL	Cash Flow from Operations/Current Liability and Provisions
	CF/SF	Cash Flow from Operations/ Shareholder's Fund
	CF/SALE	Cash Flow from Operations/Sales
	CF/TL	Cash Flow from Operations/Total Liabilities
Leverage	RE/TA	Retained Earnings/Total Assets
	SF/TA	Shareholder's Fund/Total Assets
	SF/TD	Shareholder's Fund/ Total Debt
	SF/TL	Shareholder's Fund/ Total Liability
	TL/TA	Total Liabilities/ Total Assets
Profitability	WC/TA	Working Capital/ Total Assets
	EBIT/TA	Earnings before Interest and Tax/ Total Assets
	EBIT/CL	Earnings before Interest and Tax/ Current Liabilities
	EBIT/FA	Earnings before Interest and Tax/ Fixed Assets
	EBIT/SF	Earnings before Interest and Tax/ Shareholder's Fund
	EBIT/TL	Earnings before Interest and Tax/ Total Liabilities
	NI/SALE	Net Income/ Sales
	NI/SF	Net Income/ Shareholder's Fund
Liquidity	CA/TA	Current Assets / Total Assets
	CA/CL	Current Assets / Current Liabilities
	CL/TA	Current Liabilities and Provisions/ Total Assets
	CL/SF	Current Liabilities and Provisions/ Shareholder's Fund
	CL/TL	Current Liabilities and Provisions/ Total Liabilities
	QA/TA	Quick Assets/ Total Assets
	QA/CL	Quick Assets/ Current Liabilities and Provisions
Activity	CA/SALE	Current Assets/ Sales
	INV/SALE	Inventory/ Sales
	SF/SALE	Shareholder's Fund/ Sales
	QA/SALE	Quick Assets/ Sales
	SALE/CA	Sales/ Current Assets
	SALE/TA	Sales/ Total Assets
	SALE/FA	Sales/ Fixed Assets
Market	MV/TD	Market Value of Equity/ Total Debt
	MV/SF	Market Value of Equity/ Shareholder's Fund

that can be used for developing bankruptcy prediction models for Indian companies. So this study employs 35 financial ratios, which were proved to be successful in prior studies.

Table I shows the list of ratios considered in research. This study uses financial data from the Prowess database of Centre for Management Studies, Jamia Millia Islamia University. The data sample consists of financial ratios of company's one year (Year-1), two year (Year-2) and three year (Year-3) prior to the year in which they became bankrupt. In case of non-bankrupt company, data for the same year has been considered as is considered for its matched bankrupt company.

DATA ANALYTICAL TOOLS AND TECHNIQUES

Discriminant Model

Discriminant analysis is used to classify objects/records into two or more groups based on the knowledge of some variables related to them. Discriminant function analysis or Discriminant Analysis is used to classify cases into the values of a categorical dependent, usually a dichotomy. If discriminant function analysis is effective for a set of data, the classification table of correct and incorrect estimates will yield a high percentage. Multiple discriminant analysis (MDA) is an extension of discriminant analysis and an extension of multiple analysis of variance (MANOVA), sharing many of the same assumptions and tests. MDA is used to classify a categorical dependent, which has more than two categories, using as predictors several interval or dummy independent variables. The Discriminant analysis equation is defined as-

$Y=a+k_1x_1+k_2x_2+.......+k_nx_n$.................................. (Eq. 1)

Where Y is dependent variable; a is a constant; $x_1, x_2, \ldots x_n$ are independent variables; $k_1, k_2, \ldots k_n$ are coefficients of the independent variables.

This model is used to classify or make predictions in problems where the dependent variable appears in qualitative form e.g., male or female, bankrupt or non-bankrupt etc. It represents the best way of classifying observations into one of several defined groupings – frequently known as priori groups. These groups are dependent upon the observation's individual characteristics. In this research, when classifying companies, the financial ratios are to be put into the discriminant function making up the liner combination. By comparing the discriminant values that separate bankrupt and non-bankrupt companies, one can determine which group a certain company is falling into.

Logistic Regression

It is a specialized form of regression that is formulated to predict and explain a binary (two-group) categorical variable rather than a metric-dependent measurement (Ong et.al., 2011). Logistic regression utilizes the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable (Dielman, 1996). In the context of bankruptcy prediction, this technique weighs the financial ratios and creates a score for each company in order to be classified as bankrupt or non-bankrupt. The function in logistic regression is called the logistic function and can be written as follows:

$p_i = 1 / (1+e^{-z_i})$ .... (Eq. 2)

Where

p_i = the probability of the ith case experiences of the event of interest

z_i = the value of the unobserved continuous variable for the ith case.

Neural Network

Neural networks are inspired by neurobiological systems. Robert Hecht-Nielsen, inventor of one of the earliest neurocomputers, defines a neural network as a computing system made up of several simple, highly interconnected processing elements that process information by their dynamic state responses to external inputs (Caudill, 1989). It is a function of predictors (also called inputs or independent variables) that minimizes the prediction error of target variables (also called outputs). An artificial neural network is layered; each of these layers has several neurons that are connected to other neurons belonging to the preceding and following layer (Bredart, 2014).

EMPIRICAL RESULTS

In order to identify any difference between bankrupt and non-bankrupt companies descriptive statistics are calculated based on financial ratios one year prior to bankruptcy. Table 2 presents a summary of the descriptive statistics.

Discriminant Analysis

In order to develop the discriminant analysis in this study a stepwise selection technique was employed. The stepwise process involves introducing the ratios into the discriminant function one at a time based on their discriminating power. The bankruptcy prediction models are presented below:

Year-1:

Z=4.999xSF/TA+0.963xEBIT/FA+0.731xSALE/T –.271....(Eq.3)

Year -2:

Z= 5.057xEBIT/TL + 1.053xSALE/TA – 1.743 ....(Eq. 4)

Year -3:

Z=-0.246xCL/SF + 3.862xEBIT/TL +0.882x SALE/TA–1.196 ....(Eq.5)

In the above function the cut-off point is 0. The cut-off point indicates that the company with Z score greater than 0 are predicted as non-bankrupt and the company with Z score less than 0 are predicted as bankrupt. The Model performance is evaluated using the overall accuracy rate. Overall accuracy is based on the total number of correct classifications.

TABLE 1: EMPLOYED FINANCIAL RATIOS

	Non-Bankrupt		Bankrupt		Total			
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	F	Sig.
RE/TA	0.150	0.199	-0.100	0.341	0.025	0.305	28.885	0.000**
SF/TA	0.367	0.152	0.212	0.144	0.289	0.167	39.549	0.000**
SF/TD	1.998	3.553	0.485	0.445	1.241	2.635	12.847	0.000**
SF/TL	0.876	1.090	0.343	0.310	0.610	0.842	15.925	0.000**
TL/TA	0.575	0.165	0.730	0.146	0.653	0.174	35.468	0.000**
CF/TA	0.091	0.080	0.042	0.088	0.066	0.087	12.405	0.001**
CF/CL	0.527	0.547	0.167	0.894	0.347	0.760	8.478	0.004**
CF/SF	0.283	0.288	0.343	1.741	0.313	1.244	0.083	0.773
CF/SALE	0.105	0.142	-0.002	0.312	0.052	0.248	6.936	0.009**
CF/TL	0.156	0.201	0.060	0.129	0.108	0.175	11.712	0.001**
AR/CF	3.433	22.810	-1.269	16.730	1.082	20.072	1.990	0.161
CA/TA	0.440	0.163	0.348	0.210	0.394	0.193	8.492	0.004**
CA/CL	2.441	1.365	2.461	3.199	2.451	2.451	0.002	0.961
CL/TA	0.233	0.153	0.196	0.128	0.215	0.142	2.409	0.123
CL/SF	0.846	1.077	2.170	3.481	1.508	2.652	9.512	0.002**
CL/TL	0.443	0.350	0.270	0.166	0.356	0.286	14.320	0.000**
QA/TA	0.234	0.122	0.204	0.162	0.219	0.143	1.586	0.210
QA/CL	1.254	0.753	1.355	1.609	1.304	1.253	0.234	0.629
WC/TA	0.207	0.154	0.152	0.184	0.180	0.171	3.730	0.055
EBIT/TA	0.106	0.060	-0.012	0.176	0.047	0.144	28.946	0.000**
EBIT/CL	0.611	0.539	-0.032	1.195	0.290	0.978	17.299	0.000**
EBIT/FA	0.356	0.327	-0.006	0.429	0.175	0.421	32.291	0.000**
EBIT/SF	0.334	0.242	-0.270	2.000	0.032	1.451	6.470	0.012*
EBIT/TL	0.199	0.129	-0.007	0.219	0.096	0.207	47.231	0.000**
NI/SALE	0.029	0.138	-0.567	2.494	-0.269	1.785	4.101	0.045*
NI/SF	0.099	0.186	-1.415	2.899	-0.658	2.184	19.557	0.000**
CA/SALE	0.659	1.470	0.667	0.431	0.663	1.079	0.002	0.967
INV/SALE	0.399	1.426	0.281	0.254	0.340	1.022	0.478	0.490
SF/SALE	0.515	0.600	0.629	0.914	0.572	0.773	0.786	0.377
QA/SALE	0.260	0.194	0.385	0.331	0.323	0.278	7.712	0.006**
SALE/CA	3.047	2.319	1.907	1.266	2.477	1.947	13.399	0.000**
SALE/TA	1.256	0.880	0.607	0.479	0.931	0.777	30.187	0.000**
SALE/FA	4.177	3.886	2.048	2.388	3.113	3.387	15.687	0.000**
MV/TD	2.042	3.122	0.345	0.400	1.194	2.375	20.943	0.000**
MV/SF	1.311	1.979	1.396	1.863	1.354	1.916	0.071	0.791

** 5% significant level* *** 1% significant level*

The results obtained by using multi discriminant analysis on the holdout sample are presented in Table 3 above. In one year prior to bankruptcy that is Year-1, observed non-bankrupt cases are 14 banks which were predicted as non-bankrupt but 7 banks that were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, the 7 were predicted as non-bankrupt which further observed as non-bankrupt and 16 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage is 70.45.

However, in Year-2, observed non-bankrupt are 13 banks which were predicted as non-bankrupt banks but 10 which were wrongly predicted as bankrupt ,turned out to be non-

TABLE 3: CLASSIFICATION RESULTS – MULTIPLE DISCRIMINANT ANALYSIS

			Predicted		
			Non-Bankrupt	**Bankrupt**	**Correct Percent**
Year -1	Observed	Non-Bankrupt	14	7	68.18
		Bankrupt	7	16	72.73
	Overall Percent Correct				70.45
Year-2	Observed	Non-Bankrupt	13	10	59.09
		Bankrupt	8	13	63.64
	Overall Percent Correct				61.36
Year-3	Observed	Non-Bankrupt	14	7	68.18
		Bankrupt	11	12	54.55
	Overall Percent Correct				61.36

bankrupt. Whereas, the 8 were predicted as non-bankrupt which further observed as non bankrupt and 13 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage turned out in two years prior to bankruptcy is 61.36.

The situation in three year prior to bankruptcy that is Year-3 shows that the observed non-bankrupt cases are 14 banks, which were predicted as non-bankrupt but 7 banks which were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, 11 were predicted as non-bankrupt which further were observed as non bankrupt and 12 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage turned out to be 61.36 in two years prior to bankruptcy.

It has been observed that the accuracy rate shows a declining trend from 70.45 % one year prior to bankruptcy to 61.36 % for years two and three prior to bankruptcy.

4.2 Logistic Regression

Stepwise logistic regression analysis is used to develop models for predicting corporate bankruptcy. The bankruptcy prediction models have been presented in the form of equations below:

Year-1:

Z = -6.578xSF/TA – 7.716xEBIT/TL -1.643 x SALE/TA + 4.081 …….(Eq. 6)

Year-2:

Z = -9.039xEBIT/TL - 1.065xSALE/CA+3.661…………(Eq. 7)

Year-3:

Z = 25.181xEBIT/TA–19.847xEBIT/TL – 1.178x SALE/TA + 1.189 …(Eq. 8)

The Z score obtained from the model can be transformed into a probability using the logistic transformation $P = 1/(1+e^{-z})$. The cut-off value is 0.5. It means that if the estimated probability calculated as above is greater than 0.5, the company would be predicted as bankrupt.

The results obtained by using logistic regression on the holdout sample are presented in Table 4. In one year prior to bankruptcy by applying Logistic regression is shown as Year-1, which observed non-bankrupt cases as 16 banks which were predicted as non-bankrupt but 6 banks were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, 5 were predicted as non-bankrupt which further observed as non bankrupt and 17 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage is 75.00.

However, in Year-2, observed non-bankrupt are 13 banks which were predicted as non-bankrupt banks but 9 which were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, 9 were predicted as non-bankrupt which further observed as non bankrupt and 13 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage turned out to be 59.09 in two years prior to bankruptcy.

The situation in three year prior to bankruptcy that is Year-3 shows that the observed non-bankrupt cases are 14 banks, which were predicted as non-bankrupt but 8 banks were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, 9 cases were predicted as non-bankrupt which further observed as non bankrupt and 13 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage turned out to be61.36 in two years prior to bankruptcy.

The results indicate that the accuracy rate fall from 75.00% one year prior to bankruptcy to 59.09% two years prior to bankruptcy. For the third year prior to bankruptcy the accuracy rate slightly increases to 61.36%.

Neural Network

To develop the neural network bankruptcy prediction model, the sample of 72 bankrupt and 72 non-bankrupt companies is portioned into training, testing and holdout samples. The training sample comprises the data records used to train the neural network. 40 bankrupt and 40 non-bankrupt companies were assigned to the training sample in order to obtain a model. The testing sample is an independent set of data records used to track errors during training in order to prevent overtraining. 10 bankrupted and 10 non-bankrupted companies were assigned to the testing sample. The holdout sample is another independent data set used to access the final neural network. Remaining 22 bankrupted and 22 non-bankrupted companies were assigned to the holdout sample.

The results so obtained by applying neural networks on the holdout sample are presented in the table above.

TABLE 4: CLASSIFICATION RESULTS – LOGISTIC REGRESSION

			Predicted		
			Non-Bankrupt	**Bankrupt**	**Correct Percent**
Year -1	Observed	Non-Bankrupt	16	6	72.73
		Bankrupt	5	17	77.27
	Overall Percent Correct				75.00
Year-2	Observed	Non-Bankrupt	13	9	59.09
		Bankrupt	9	13	59.09
	Overall Percent Correct				59.09
Year-3	Observed	Non-Bankrupt	14	8	63.64
		Bankrupt	9	13	59.09
	Overall Percent Correct				61.36

TABLE 5: CLASSIFICATION RESULTS – NEURAL NETWORK

			Predicted		
			Non-Bankrupt	**Bankrupt**	**Correct Percent**
Year -1	Observed	Non-Bankrupt	20	2	90.91
		Bankrupt	8	14	63.64
	Overall Percent Correct				77.27
Year-2	Observed	Non-Bankrupt	13	9	68.18
		Bankrupt	9	13	59.09
	Overall Percent Correct				63.64
Year-3	Observed	Non-Bankrupt	14	8	81.82
		Bankrupt	9	13	50.00
	Overall Percent Correct				65.91

However, in Year-2, observed non-bankrupt are 13 banks but 9 which were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, 9 were predicted as non-bankrupt which further observed that 13 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage turned out to be 63.64 in two years prior to bankruptcy..

The situation in three year prior to bankruptcy that is Year-3 shows that the observed non-bankrupt cases are 14 banks, which were predicted that 8 banks were wrongly predicted as bankrupt, turned out to be non-bankrupt. Whereas, 9 cases were predicted as non-bankrupt which further observed as non bankrupt and 13 were predicted correctly as bankrupt. Thus, the overall correct prediction percentage turned out to be 65.91 in two years prior to bankruptcy.

It has been observed that the model's accuracy rate falls from 77.27% one year prior to bankruptcy. However, the rate fell down to 63.64% two years prior to bankruptcy and then rises to 65.91% for the third year to bankruptcy.

Comparison of Results

This section compares the results of the three different methods used in this research and that is shown in the table below.

These results presented in table above indicate that neural network achieved the highest overall classification accuracy for all the three years prior to bankruptcy. Multiple discriminant analysis and logistic regression produce comparable results. This is so because neural networks have highly interconnected processing elements which process information by their dynamic state responses to external inputs.

TABLE 6: COMPARATIVE RESULTS OF THE BANKRUPTCY TECHNIQUES TESTED

	Multiple Discriminant Analysis	**Logistic Regression**	**Neural Network**
Overall Percent Correct			
Year-1	70.45	75.00	77.27
Year-2	61.36	59.09	63.64
Year-3	61.36	61.36	65.91

ONCLUSION

In this study the companies that were delisted from Bombay Stock Exchange or National Stock Exchange and who's latest net worth and the net worth prior to the year of delisting is negative were taken. And for the bankrupt companies the year of bankruptcy was the year in which its net worth became negative. Financial institutions delisted companies merged with other companies and companies for whom at least three years full financial statements prior to the year of bankruptcy were not available are excluded from this research.

Due to major structural changes that took place in the Indian economy from 1991, the study period considered is from 1991 to 2016. With the application of bankruptcy as mentioned above in this duration, 72 companies resulted in a sample as bankrupt. Similar to Altman's (1968) study's procedure, a twin company was chosen up that was not bankrupt from the same industry and approximately matched for asset size prior to the year of bankruptcy. This process has also been applied in majority of previous bankruptcy prediction studies. In order to develop bankruptcy models the companies are matched or made pairs so as to isolate key factors which distinguish otherwise similar firms (Morris, 1997). Thus, the total sample consisted of 138 companies.

The bankrupt and non-bankrupt companies are randomly divided to create distinct analysis and holdout samples. The analysis sample contains 50 bankrupt and 50 non-bankrupt companies and the holdout sample contains 22 bankrupt and 22 non-bankrupt companies.

This research attempts to develop and compare the performance of bankruptcy prediction models using multiple discriminant analysis, logistic regression and neural network for Indian listed companies. The dataset consists of 72 matched pairs of bankrupt and non-bankrupt companies. The bankrupt companies had failed between the periods of 1991 and 2016. Accuracy rates for one, two and three years prior to bankruptcy for neural network are 77.27, 63.64 and 65.91 percent respectively, and for logistic regression the values are 75.00, 59.09 and 61.36 percent. However, the accuracy rates for the multiple discriminant analysis are 70.45, 61.36 and 61.36 percent.

The results have shown that compared to multiple discriminant analysis and logistic regression, the neural network has the highest prediction accuracy for all the three years prior to bankruptcy. This is so because neural networks have highly interconnected processing elements which process information by their dynamic state responses to external inputs. Thus being so, it is suggested that neural network modeling should be used as successful bankruptcy predictor in case of Indian companies.

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