

Models for Prediction of Industrial Insolvency of Manufacturing Companies in India

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Abstract

Investors, activists and corporations across the world are emphasizing on prediction of insolvency well in advance so that corrective actions can be taken and erosion of funds can be prevented. For this purpose, this study attempts to construct models for forecasting industrial sickness and to validate the performance of these models. This paper proposes new models for prediction of industrial sickness or leading bankruptcy using three different techniques i.e. a model using Multi Discriminant Analysis (MDA), a model using MDA + PCA (Principle Component Analysis), and a model using ANN (Artificial Neural Network). This paper focuses to propose prediction models for bankruptcy which contribute more to this impact in emerging economies like India.

The results show that the forecasting ability of the models is higher than the empirical models already available such Altman's Z score model, Ohlson's model and model developed by Odom and Sharda to name a few. The prediction accuracy of MDA model is highest among proposed models for prediction of industrial sickness. These results are recommended to financial institutions, banks and executives. This study may also be used for evaluating the repayment behavior of a borrower. These models may be used by the potential investors for screening out undesirable investments. Since the models are of predictive nature, the

investors may use it for portfolio selection.

Keywords: bankruptcy prediction, insolvency, accounting ratios, neural network, multi-discriminant, PCA.

JEL Classification: G33, C02, C38, C45, C52, C53

1. Introduction

The achievement of success had been the enunciation in management research for last few decades. The companies had been judged on the basis of how rapidly they had grown and how fast they increased their market share. The bankruptcy or insolvency of a company has been a very important part of a manager's job as the accomplishment of its success. This role is becoming more significant and crucial as the penalties of failure are becoming more modest.

A number of activities are performed in the business by each company. But the outcomes of certain activities are uncertain and risky. This involves risk for every business. "Among the different risks that an organization is faced with, default risk is possibly one of the ancient financial risks, though there have not been many instruments to manage and hedge this type of risk till recently" (Gupta, 2014).

The majority business transactions are of financial nature (Yadav, 1986) which leads to default risk and finally results into non-repayment of debt. Default risk has gained utter importance because of innovative financial instruments, different tools of risk management and change in economic conditions. The risk of default is at the center of credit risk: Credit rating agencies (CRAs) are the most important supply for measuring the credit superiority of businesses/borrowers in developing economies like Asian countries. Since improvement and deterioration of ratings will influence the worth of equity and debt that is being listed within the market, participants of area unit are fascinated in developing sensible models for prediction.

The failure of a firm brings stress to entrepreneurs, managers and the society at large. The unemployment goes up, availability of goods and services goes down, the cost goes up and a large sum of funds is blocked up. The shareholders lose their investments, creditors lose their funds the customer is deprived of the product. Therefore, a model is required which predicts the insolvency at the earliest and would serve to minimize such losses by providing alarm and a warning in advance to all the concerned parties. This requirement has been the primary motivation for us to investigate the prediction of industrial insolvency as an interesting area.

With a small improvement in assessing the credit risk, reduction in a considerable amount of savings for an economy can be achieved. (Lee and Choi, 2013). An improvement in the accuracy of even a fraction of percent in scoring of models, to estimate the probability of default leads to enormous future savings for the credit industry. (West, Dellana and Qian, 2005).

Though a wide number of analytical/mathematical/statistical models are present, there was a great emphasis to be given to an emerging economy like India to develop bankruptcy forecasting model. There are numerous models developed over the years due to growing data availability and development of econometrical techniques during the decades of 80s and 90s. There are two groups in which methods of bankruptcy prediction can be categorized: statistical models and intelligent models. The statistical models include the formalization of relationships between variables in the form of mathematical equations whereas intelligent

models include machine learning which includes an algorithm that can learn from data without rules-based programming. The statistical models include MDA, logit regression etc. The first techniques applied to insolvency forecasting was the univariate data analysis (Beaver, 1966) followed by the multi discriminant analysis (Altman, 1968) and logit regression (Ohlson, 1980). The second group consists of principal component analysis (PCA), artificial neural networks (Chauhan, Ravi & Chandra, 2009; Cho, Kim & Bae, 2009; Pendharkar, 2005; Ravishankar & Ravi; 2010; Kim & Kang, 2010; Tseng & Hu, 2010; Lee & Choi, 2013), genetic algorithms (Lensberg, Eilifsen & McKee, 2006; Etemadi, Rostamy & Dehkordi, 2009; Ahn & Kim, 2009), support vector machines (SVM) (Min & Lee, 2005; Hardle, Lee, Schafer, & Yeh, 2009; Yang, You & Guoli Ji, 2011) and case based reasoning (Ahn & Kim, 2009; Cho Hong & Ha, 2010; Li & Sun, 2010, 2011; Li, Adeli, Sun, & Han, 2011)

This paper exhibits the detailed analysis of the construction and validation of the models for prediction of industrial sickness. The analysis is organized into five sections. The first section shows the detailed description of the financial ratios for non-sick and sick companies. The second section deals with various statistical tests which show the financial ratios as discriminators. The third section involves the analysis of the predictor ratios. The fourth section presents a comprehensive discussion of the model construction for prediction of industrial sickness using different methodologies. Finally, the last section shows the validation of the models and their accuracy results.

The purpose of the study is to assess the projecting capability of four insolvency forecasting models for manufacturing firms which are listed on stock exchanges: a discriminant analysis using J-Score, a proposed model using MDA+PCA and a proposed model using artificial intelligence.

2. Literature Review

Previous research studies have used several financial ratios to different sample sets in various countries to study prediction of corporate sickness. Beaver (1966) found out that cash flow to total debt ratio exhibited statistically significant warnings prior to business failure and concluded that the firms with lower liquid assets were more prone to bankruptcy and vice versa. The study also suggested the possibility of using multiple ratios simultaneously in order to have the higher predictive ability. Altman (1968) proved that a prediction model based on multiple discriminant analysis had been extremely accurate in predicting bankruptcy. The majority of the studies found that debt and profitability related ratios significantly determine the corporate failure.

Gupta (1983) concluded that net worth to short and long term debt and outside liabilities to tangible assets ratios were useful in predicting corporate failure. Kumar and Kumar (2012) found that Ohlson's O-Score model using binary logistic regression technique performed better than Altman's model and suggested the possibility of using domestic data through new models based on different combinations of financial ratios.

Many researchers have employed Multiple Discriminant Analysis (Gupta, 1983; Lincoln,

1984; Izan, 1984) and logit analysis (Mohamed, Li, and Sanda, 2001; Abdullah, Hallim, Ahmad and Rus, 2008) in determining the predictors of corporate failure. Some of these studies have compared the results of Multiple Discriminant Analysis and Logit Analysis. Early Warning models for predicting corporate bankruptcy have been developed by some of these researchers.

In the past, several studies indicated various financial ratios as predictors of corporate sickness. Patrick (1932) showed that the net worth to debt and net profits to net worth were the best indicators of failure among the ratios used. The financial ratios commonly used by researchers were net income to total assets (Beaver, 1966; Deakin, 1976; Libby, 1975; Ohlson, 1980; Lennox, 1999), total liabilities to total assets (Beaver, 1966; Deakin, 1976; Ohlson, 1980; Zmijewski, 1984). Net income ratio was used to represent growth. In UK context, Lennox (1999) used cash to current liabilities, debtor turnover ratio and gross cash flow ratio as the predictors. The bankruptcy in Korea studied by Nam and Jinn (2000) revealed that it was due to financial expenses to sales, debt coverage and receivables turnover ratio.

We have reviewed different research studies which were relevant to the current work under wide areas. Beaver (1966, 1968) and Altman (1968) had developed the first set of accounting models to measure the bankruptcy threat for a firm. Beaver (1966) had developed a univariate model for forecasting indebtedness of a firm. Altman (1968) had developed a model by adopting discriminant analysis with the use of financial ratios for discretion between insolvent and solvent firms. Later Altman et al. (1977) developed z-score models called ZETA and another model was developed by Altman et al. (1995) for the companies/firms in emerging markets. A study was conducted in 22 countries by Altman and Narayanan (1997) where they concluded that the default risk can be predicted effectively with the ratios based models.

Recently, Gupta (2014) had developed an accounting based prediction model using discriminant analysis and logit regression and compared the predictive ability of these models. “For logistic regressions, an attempt was made to combine macro variables and dummy industry variables along with accounting ratios. The paper had analyzed that the predictive ability of the proposed Z-score model was higher when compared to both the Altman original Z-score model and the Altman model for emerging markets. The research findings establish the superiority of logit model over discriminant analysis and demonstrate the significance of accounting ratios in predicting default.” (Gupta, 2014)

The first attempt to use ANNs to predict bankruptcy was made by Odom and Sharda (1990). In their study, three-layer feed forward networks were used and the results were compared to those of multivariate discriminant analysis. Using different ratios of bankrupt firms to non-bankrupt firms in training samples, they test the effects of different mixture level on the predictive capability of neural networks and discriminant analysis. Neural networks are found to be more accurate and robust in both training and test results.

A number of network training parameters are varied to identify the most efficient training paradigm. The focus of this study is mainly on the improvement in efficiency of the back propagation algorithm. Coleman et al. also report improved accuracy over that of Odom and

Sharda (1990) by using their Neural Ware ADSS system.

Boritz et al. (1995) use the algorithms of back propagation and optimal estimation theory in training neural networks. The benchmark models by Altman (1968) and Ohlson (1980) are employed. Results show that the performance of different classifiers depends on the proportions of bankrupt firms in the training and testing data sets, the variables used in the models, and the relative cost of Type I and Type II errors. Boritz and Kennedy (1995) also investigate the effectiveness of several types of neural networks for bankruptcy prediction problems.

Cheng, Chen, and Fu (2006) predicted corporate bankruptcy by combining logit model with neural network, which avoids drawbacks of both methods and incorporate advantages of both methods. Hua, Wang, Xu, Zhang, and Liang (2007) adopted logistic regression to minimize the risk of support vector machine in prediction of business failure. Sun and Li (2008b) constructed multi-classifiers system for bankruptcy prediction using MDA and logit as components.

Lee and Choi (2013) used back-propagation neural network (BNN) for investigating multi-industry bankruptcy of Korean companies. The study intended on suggesting the industry specific model to predict bankruptcy by selecting appropriate independent variables. They compared the prediction accuracy of BNN to multivariate discriminant analysis. According to their study, the industry sample has better performance of prediction than the non-classified sample by the variation of 6 - 12%. The prediction accuracy of bankruptcy using BNN was found better than that of MDA.

Principal component analysis (PCA) is an expedient statistical technique for feature extraction. PCA can help a classifier produce more accurate predictive performance (Avcı & Turkoglu, 2009). It is assuming that most of information about classification is contained in the directions along which the feature values are the largest (Polat & Günes, 2008). The component scores and loadings can be used to interpret the results of a PCA (Shaw, 2003).

Li and Sun (2011) constructed a new hybrid model for bankruptcy prediction by integrating principal component analysis (PCA) with MDA and logit to have better predictive performance. This study has followed data mining approach, case based reasoning, neural network, support vector machine technique and discriminant analysis based on previous studies (for example, Jo, Han, & Lee, 1997; Li, Sun, & Sun, 2009; Lin & McClean, 2001; Min & Lee, 2005; Min, Lee, & Han, 2006; Sun & Li, 2008a) without differentiating type I and type II errors. They have done a pilot study which demonstrated the use of PCA with MDA and logit in bankruptcy prediction. The model was developed by using stepwise method of MDA, stepwise method of logit, and independent sample t test as the preprocessing procedure, on the basis of which PCA is further used to extract features for MDA and logit. They have obtained the optimal preprocessing procedure by splitting the available data for 30 times for PCA. This model was used to investigate the bankruptcy prediction of listed companies of China. The results show that the hybrid model of PCA with MDA and logit has better prediction power and it has outperformed all other models.

After a comprehensive literature review on bankruptcy prediction, it was found that a plenty of work had been done in this area but we can see a gap in development of prediction models for manufacturing sector in emerging economies like India. Though there are models available in the Indian context, but these models are quite old and are constructed adopting the financial ratios which had been used in the previous studies decades back. As the businesses have changed, there has been a change in the financial ratios affecting the solvency of the companies. The research gap for this study is to identify the financial ratios which are discriminating between sick and non-sick companies and use those financial ratios as predictive variables of industrial sickness. It had been found from the literature that the discriminating financial ratios between sick and non-sick companies have changed over the year in different studies. We are focusing on constructing and validating the prediction models using such discriminating variables.

Given the research gap, this study emphasizes to construct and validate bankruptcy prediction models using different financial ratios with a high predictive power and generalized applicability. For this purpose, we have formulated following hypotheses:

Hypothesis 1: There is no significant difference between mean values of financial ratios of non-sick and sick companies. (For determination of discriminators)

Hypothesis 2: The financial ratios do not predict industrial sickness. The predictors have no significant effect on either of the outcomes, namely sick and non-sick. (For determination of predictors)

Hypothesis 3: The prediction models are not capable of making correct predictions of industrial sickness.

3. Methodology

This study emphasizes on development of a forecasting model using various techniques. For this purpose, secondary data was collected from the financial statements of the companies from ACE Equity database. A sample was obtained on the basis of the credit ratings given by the credit rating agencies. A sample of 80 companies was obtained in which the companies were stratified as far different industries pertaining to manufacturing sector. Entire sample was divided on the basis of their credit ratings of the financial year ending on March 31, 2014, signifying their solvency position. Out of the entire sample, there were 40 companies which were given lowest ratings (Credit Rating: D) by the agencies (failed/defaulted companies) and other 40 companies which belonged to the same industries and of same size and were given highest ratings by the agencies (Credit Rating: AAA) (non-failed/solvent companies). Out of the total sample size, we have used a sample of 50 firms (25 firms of each category of solvent and insolvent companies) as the training sample. Whereas the remaining 30 companies were used as the holdout or validation sample. Following Table 1 provides the number of companies selected as a sample from different industries for the purpose of this study. This study covers manufacturing companies of India which are listed on stock exchanges. Service sector companies have been excluded from the sample.

Table 1. List of Companies in Dataset/Sample

Industry	No. of Companies
Electricals	4
Chemicals	6
Pharmaceuticals	20
Textile	18
Machinery	12
Consumer Food & Sugar	12
Cement & Metals	6
Others	2
Total	80

3.1 Methodology for Selection of Variables

A set of 56 ratios were taken on the basis of previous literature such as (Altman, 1968; Ohlson, 1980; Gupta, 1983) for the years 2009 - 2013 from financial statements of the companies for identifying the ratios which discriminate between sick and non-sick companies. These ratios involve various categories such as liquidity ratios, solvency ratios, and profitability ratios, productivity ratios, operating efficiency ratios, leverage ratios, growth ratios, and net worth ratios, turnover ratios and cash flows ratios.

3.2 Determination of Discriminators for Industrial Sickness

To construct a model for prediction of industrial sickness, the initial step is to identify and determine the financial ratios which discriminate significantly between non-sick and sick companies.

The financial ratios should fulfill following conditions for determination of discriminators.

1. The sample must be normally distributed
2. The samples must have equal variances
3. The observations of samples should be independent of each other, within the groups and between the groups.

Test of Normality has been used to find out if financial ratios of both sick and non-sick companies were normally distributed. Spearman's correlation coefficient was used to find out if the ratios were independent ones. Test of equality of variance was carried out to observe if financial ratios have equal variances between sick and non-sick companies.

The parametric tests which we apply in this study examine the difference between the two group means and conclude whether there exists a significant difference between the two distributions.

As seen in the previous studies (e.g. Gnanadesikan and Kettenring 1972, Belsley et al. 1980, Laitinen, 1991), the requirement of normality has been frequently violated in the case of distributions of financial ratios in several previous studies and even transformation of the data to approximate normality did not improve normality in all cases. If the above mentioned conditions are not met and when majority of the ratios are found to be of non-normal distribution, non-parametric tests can be applied. The distribution of the non-parametric test statistics may give a more reliable result (Laitinen E., 1991). Non-parametric tests use ranks of the variables to compare medians rather than means. This consideration facilitated the use of parametric statistical tests in the present study.

For selection of variables, first, the normality of data was checked using Anderson-Darling Normality Test. The results showed that majority of the ratios were normally distributed. For the purpose of analyzing the equality of variances between two samples of sick and non-sick companies, Levene's test of equality of variance was performed. The correlation coefficient was calculated between two samples to avoid multi-collinearity and it was found that most of the variables have low correlations with each other.

Using the results of the of independent two sample t - test and MANOVA, emerging discriminators were identified. It is including the financial ratios which were discriminators between non-sick and sick companies in the years i.e. 2009 - 2013 prior to the year 2014 in which their credit rating was showing them industrially sick.

Financial ratios were identified as discriminators on the basis of the analysis of independent two sample test and the results of MANOVA. Out of the analysis, there are total 32 ratios who have come out as emerging discriminators from the results of independent two sample t test. We have also taken 9 other financial ratios which were not emerging as discriminators as a result of independent t - test but found to be significant according to MANOVA analysis whose p value is less than 0.05. There are total 41 financial ratios who have been identified as discriminators shown in the table below.

Table 2. Summary of Financial Ratios Identified as Discriminators

Variable	Description of Ratios	Variable	Description of Ratios
R ₁	Retained Earnings/Total Assets (RE/TA)	R ₂₁	Total Tangible Assets/Total Debt (TTA/TD)
R ₂	Interest Coverage Ratio (ICR - based on Earnings Before Interest, Taxes, Depreciation and Amortization)	R ₂₂	Total Tangible Assets/Long-term Debt (TTA/LTD)
R ₃	Debt - Equity Ratio (D/E)	R ₂₃	Net Worth/Total Debt (NW/TD)
R ₄	Net Sales/Total Assets (NS/TA)	R ₂₄	Cash/Total Tangible Assets (Cash/TTA)
R ₅	Earnings Before Interest and Taxes/Total Assets (EBIT/TA)	R ₂₅	Quick Assets/Total Tangible Assets (QA/TTA)
R ₆	Profit After Taxes/Total Assets (PAT/TA)	R ₂₆	Current Assets/Total Tangible Assets (CA/TTA)
R ₇	Profit After Taxes/Net Sales (PAT/NS)	R ₂₇	Cash/Current Liabilities (Cash/CL)
R ₈	Profit Before Depreciation and Interest After Taxes/Net Sales (PBDITA/NS)	R ₂₈	Net Sales/Debtors (NS/Debtors)
R ₉	Market Value of Equity/Book Value of Liabilities (MVE/BVL)	R ₂₉	Net Sales/Inventories (NS/Inv.)
R ₁₀	Book Value of Equity/Book Value of Liabilities (BVE/BVL)	R ₃₀	Net Sales/Fixed Assets (NS/FA)
R ₁₁	Total Debt/Total Assets (TD/TA)	R ₃₁	Cash/Total Operating Expenditure (Cash/TOE)
R ₁₂	Fixed Cost/Total Assets	R ₃₂	Earnings Before Interest and Depreciation and

	(FC/TA)		Taxes/(Total Assets + Depreciation) [EBIDT/(TA+DEP)]
R ₁₃	Earnings Before Interest and Taxes/Total Tangible Assets (EBIT/TTA)	R ₃₃	Operating Cash Flow/(Total Assets + Depreciation) [OCF/(TA+DEP)]
R ₁₄	Net Sales/Total Tangible Assets (NS/TTA)	R ₃₄	Net Worth/Total Tangible Assets (NW/TTA)
R ₁₅	Operating Cash Flow/Total Tangible Assets (OCF/TTA)	R ₃₅	Current Ratio (CR)
R ₁₆	Operating Cash Flow/Total Debt (OCF/TD)	R ₃₆	Quick Ratio (QR)
R ₁₇	Profit After Taxes/Total Tangible Assets (PAT/TTA)	R ₃₇	Profit After Taxes/Capital Employed (PAT/CE)
R ₁₈	Profit After Taxes/Total Debt (PAT/TD)	R ₃₈	Current Liabilities/Total Assets (CL/TA)
R ₁₉	Earnings Before Interest and Taxes/Interest (EBIT/Int.)	R ₃₉	Profit After Taxes/Net Worth (PAT/NW)
R ₂₀	Total Tangible Assets/Current Debt (TTA/CD)	R ₄₀	Net Assets/Quick Assets (NA/QA)
		R ₄₁	Operating Cash Flows/Net Sales (OCF/NS)

The discriminators identified in the present study align with the findings of Beaver (1966) that non-parametric analysis resulted in five ratios namely Cash flow to total debt, Net income to total assets ratio along with two other ratios discriminating between non-sick and sick companies; Gupta (1983) on the basis of a simple non-parametric test found that Operating Cash flow to (Total Assets + Depreciation), Net Worth to Total Tangible Assets and EBDIT to (Total Assets + Depreciation) as few of the seven ratios having differentiating power. The results of the discriminators of the present study support the findings of Altman (1968) where four out of five ratios of Altman's Z score model are found to be discriminating between non-sick and sick companies.

3.3 Determination of Predictors for Industrial Sickness

After identifying the discriminating financial ratios, the procedure was conducted to identify the financial ratios that are significant in the prediction of industrial sickness. This section is emphasizing on the other objective of determination of financial ratios that are important in prediction of bankruptcy. We have used canonical correlation analysis, Wilk's Lambda and mean difference of 41 financial ratios to identify significant predictors.

From this analysis, we found two sets of ratios which have emerged as the predictors. Out of these two sets, one set is having 16 ratios and another set is having 22 ratios. Following discussion focuses on identification of the financial ratios which are significant predictors of industrial sickness.

3.3.1 Canonical correlation is used for ratio selection in present study

The canonical correlation for each ratio of solvent and insolvent company is calculated. Initially, we found 22 linear combinations (22 ratios for solvent and insolvent companies) out of 41 ratios that maximize the correlations between the members of each canonical variate pair. Then we adopted a method of substituting or removing a ratio out of these 22 pairs to find out how the canonical correlation changes. After substituting the pairs of ratios, we found that there are other 16 linear combinations for which the correlation is very high. If the ratios were reduced more than 16, the correlation was affected. Therefore, we identified the values of two sets of linear combinations where canonical correlation for 16 and 22 ratios clearly show that they are highly correlated.

These two groups of ratios which were identified as predictors contain partly the same variables. There are 16 financial ratios which are same in both the groups and 6 other ratios were identified on the basis of significant canonical correlation and added in the group of 16 ratios to make 22 ratios. Furthermore, these 16 ratios and 22 ratios of the firms were used as predictors to develop different models i.e. a model using 16 ratios and a model using 22 ratios to check which model has a better predictive ability.

3.3.2 Wilk's Lambda is used in the study

Wilk's Lambda was calculated for 16 and 22 ratios both. The value for 16 ratio is 0.47593 and 22 ratio is 0.38993. The inputs are the 16 dimensional or 22 dimensional vectors of average data of solvent and insolvent companies for last 5 years.

3.3.3 Mean Difference is used in the study

Average of each ratio is taken for last five years for solvent and insolvent companies. The ratios which showed the highest difference between two classes were selected as predictors.

Out of the 41 ratios which were identified as discriminators, there are 22 ratios which have emerged as significant predictors based on canonical correlation, Wilk's Lambda and mean difference. The findings of the study are supporting the results of Datta (2013) who had used canonical correlation to identify the financial ratios which are emerging as discriminators and predictors. In the same study, Wilk's Lambda was used to determine predictors. The findings

of the study are also in line with the findings of the study done by Mahalkshmi A. (2013) who had used Wilk's Lambda, Pillai's trace and MANOVA for identifying predictors. The 22 ratios which have emerged as predictor ratios are shown in the table below.

Table 3: Summary of Financial Ratios Identified as Predictors

Variable	Description of Ratios	Variable	Description of Ratios
R ₁	CR	R ₁₂	NS/Debtors
R ₂	QR	R ₁₃	NS/Inv.
R ₃	FC/TA	R ₁₄	NA/QA
R ₄	CL/TA	R ₁₅	NS/FA
R ₅	PAT/CE	R ₁₆	Cash/TOE
R ₆	PAT/NW	R ₁₇	PBDIT/NS
R ₇	TTA/CD	R ₁₈	OCF/NS
R ₈	TTA/LTD	R ₁₉	NW/TD
R ₉	Cash/TTA	R ₂₀	EBIDT/(TA+DEP)
R ₁₀	QA/TTA	R ₂₁	OCF/(TA+DEP)
R ₁₁	CA/TTA	R ₂₂	NW/TTA

These 22 ratios are used to construct models using MDA technique where one model was created using the first 16 ratios in the above list and another model was constructed using all 22 ratios by including the remaining 6 ratios. For models using MDA + PCA and neural networks, we have used 22 ratios.

4. Development of Models

4.1 Multi Discriminant Analysis

MDA based model was first propounded by Altman (1968) as multivariate model on the basis of 5 financial ratios which had become a widely accepted tool for prediction of industrial sickness. The model construction on the basis of MDA is based on the empirical studies done by Altman (1968), Srivastava and Yadav (1986), Altman (1977) etc.

MDA is used when Dependent Variable is categorical and Independent Variables are metric.

In our case, dependent variable is the solvency of a company which is categorical and independent variables are company's different financial ratios.

MDA drives variate that best distinguishes between priori groups. MDA sets variate's weights to maximise between group variance rather than within group variance. Thus it creates the large distance between the groups.

In MDA, with the help of derived coefficients of each of the independent variables, a J score is calculated. Average J score of a group gives the centroid. Thus the classification J score is determined by cutting scores which are derived from group centroids.

MDA is a technique for measuring the probability of insolvency. This method assigns independent observations to groups defined by a qualitative feature as sick or non-sick. For this purpose, MDA develops a linear combination of inputs which can be called discriminating variables between the groups. MDA works as a classification technique with a capacity to analyse the descriptive importance of financial ratios. The percentage of firms which are correctly classified on the basis of such discriminant function shows the explanatory power of the model which is equivalent to R^2 in the regression equation.

In the MDA based model, multivariate Gaussian distribution is used to generate data using each class. The data (X) is assumed to have a normal distribution. In case of a linear MDA, each class will have equal covariance matrix in the model but the mean values will differ. Whereas in case of quadratic MDA, each class will have different covariance and mean values.

4.1.1 Model Preparation

In the MDA based model, multivariate Gaussian distribution is used to generate data using each class. The data (X) is assumed to have a normal distribution. In case of a linear MDA, each class will have equal covariance matrix in the model but the mean values will differ. Whereas in case of quadratic MDA, each class will have different covariance and mean values.

In the first step, sample mean will be calculated for each class for linear MDA. After that, sample covariance will be calculated by subtracting the mean of each class from the observations of that class and considering the experimental covariance matrix. It does not use prior probabilities or costs for fitting.

The weighted classifiers will be constructed in the model by adopting the following procedure. Suppose M is an N -by- K class membership matrix:

$M_{nk} = 1$ if observation n is from class k

$M_{nk} = 0$ otherwise.

The estimated mean value of the class for un-weighted data

$$\hat{\mu}_k = \frac{\sum_{n=1}^N M_{nk} X_n}{\sum_{n=1}^N M_{nk}} \quad (1)$$

Calculation of natural generalization for weighted data having positive weights W_n

$$\hat{\mu}_k = \frac{\sum_{n=1}^N M_{nk} W_n X_n}{\sum_{n=1}^N M_{nk} W_n} \quad (2)$$

The unbiased estimate of the pooled-in covariance matrix for un-weighted data is

$$\hat{\Sigma} = \frac{\sum_{n=1}^N \sum_{n=1}^N M_{nk} (x_n - \hat{\mu}_k)(x_n - \hat{\mu}_k)^T}{N - K} \quad (3)$$

For quadratic discriminant analysis, model uses $K = 1$.

For weighted data, assuming the weights sum to 1, the unbiased estimate of the pooled-in covariance matrix is

$$\hat{\Sigma} = \frac{\sum_{n=1}^N \sum_{n=1}^N M_{nk} W_n (x_n - \hat{\mu}_k)(x_n - \hat{\mu}_k)^T}{1 - \sum_{k=1}^K \frac{W_k^2}{W_k}} \quad (4)$$

Predictor uses three quantities to classify observations: Posterior Probability, Prior Probability, and Cost. Predict classifies so as to minimize the expected classification cost:

$$\hat{y} = \arg \min \sum_{k=1}^K \hat{P}(k/x) C(y/k) \quad (5)$$

Where

- \hat{y} is the predicted classification.
- K is the number of classes.

- $P(k/x)$ is the posterior probability of class k for observation x and
- $C(y/k)$ is the cost of classifying an observation as y when its true class is k .

The space of X values divides into regions where a classification Y is a particular value. The regions are separated by straight lines for linear discriminant analysis.

Posterior Probability

The posterior probability that a point x belongs to class k is the product of the prior probability and the multivariate normal density. The density function of the multivariate normal with mean μ_k and covariance Σ_k at a point x is

$$P(x/k) = \frac{1}{(2\pi)^{p/2} |\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)\right) \quad (6)$$

Let $P(k)$ represent the prior probability of class k . Then the posterior probability that an observation x is of class k is

$$\hat{P}(k/x) = \frac{P(x/k)P(k)}{P(x)} \quad (7)$$

Where $P(x)$ is a normalization constant, namely, the sum over k of $P(x/k)P(k)$.

With DA grouping and classification, two costs are associated, i.e. the true misclassification cost per class and the anticipated misclassification cost per observation. The cost of classifying an observation into class is b if its true class is a where it is cost (a, b) . In other words, the cost is 0 for correct classification, and 1 for incorrect classification.

After you create a classifier objective you can set a custom cost using dot notation:

$$\text{Objective Cost} = L;$$

L is a square matrix of size K -by- K when there are K classes. You do not need to retrain the classifier when you set a new cost.

Anticipated Misclassification Cost per Observation.

Each row of the cost matrix contains the expected (average) cost of classifying the observation into each of the K classes. Cost (n,k) is

$$\sum_{i=1}^k \hat{P}(i/X_{new}(n))c(k/i) \quad (8)$$

Where

- K is the number of classes.
- $\hat{P}(i/X_{new}(n))$ is the posterior probability of class i for observation $X_{new}(n)$.
- $C(k|i)$ is the cost of classifying an observation as k when its true class is i .

Back et al. (1996) stated that MDA focuses to construct a linear combination of predictors which are able to discriminate between groups of sick and non-sick companies. It may be achieved through maximization of between the group variance as compared to within the group variance. This association can be explained by the Fisher's discriminant function in the following form:

$$J(w) = \frac{w^T (\sum_i (x_i - \mu)^T (x_i - \mu)) w}{w^T (\sum_c \sum_{i \in c} (x_i - \mu_c)^T (x_i - \mu_c)) w} \quad (9)$$

In the process, sample mean will be calculated for each class for linear MDA. After that, sample covariance will be calculated by subtracting the mean of each class from the observations of that class and considering the experimental covariance matrix. It does not use prior probabilities or costs for fitting.

Three MDA functions are constructed using the methodology described above. These models are constructed using a set of 16 ratios, a set of 22 ratios and a set of 22 ratios along with PCA. These models are named as J - Score models and the threshold limits/cut-off points for all the models are identified which results in minimum number of misclassifications. The discriminant function used in this study indicating the linear combination of independent variables as follows:

$$J = a_0 + a_1 x_1 + a_2 x_2 + \dots + a_n x_n \quad (10)$$

Hair et al. (2006) defined the threshold limits as the dividing point which will be used to categorize observations into groups based on the function scores. The threshold point between two groups is calculated on the basis of the group centroids and size of the groups. The optimum threshold limit assuming equal size of two groups with prior probabilities of 0.5 can be calculated as follows:

$$Cut - off = \frac{N_A Z_B + N_B Z_A}{N_A + N_B} \quad (11)$$

The above formula shows the optimal cut off score between groups A and B, where N_A , N_B are sizes of group A and B, Z_A , Z_B are centroids for both groups A and B, respectively.

The J Score thresholds/cut-off points for three models are given below.

- ✓ 16 Ratio Model using MDA: Threshold=0
- ✓ 22 Ratio Model using MDA: Threshold=0.33
- ✓ MDA+PCA Model using 22 ratios: Threshold=0.3

The major disadvantages of MDA over other methods include statistical or methodological issues which hinders the practical applicability of the models. Such issues include (i)

dispersions of the group, (ii) the classification error estimations, (iii) the costs of misclassifications and appropriate a priori probabilities, (iv) dimension reduction, (v) the distribution of variables, (vi) the groups' definitions, and (vii) the inference of variable's significance.

4.2 Principal Component Analysis (PCA)

Principal Component Analysis is a technique used to express a relationship in the data when there are many variables and a significant relationship can be developed. PCA as a technique helps us to reduce the large number of variables with much lesser number of variables that represents the same data more effectively. In this study, we have used PCA as a dimension reduction technique. Such lesser number of simulated/synthetic variables are called principal components.

PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analysing data.

The other main advantage of PCA is that once you have found these patterns in the data, and you compress the data, i.e. by reducing the number of dimensions, without much loss of information.

The previous studies by Alici (1996) and Rekha Pai, Vijayalakshmi Pai and Annapoorani (2006) on the application of Principal Component Analysis (PCA) for the prediction of industrial bankruptcy has shown potential of PCA in prediction of industrial sickness. As per their study, PCA not only works as a method for dimension reduction but also shows better predictive ability. In the present study, PCA had been adopted for the pattern recognition, dimension reduction and prediction of industrial sickness.

PCA is a useful statistical technique for pattern recognition and data compression. PCA makes use of multiple statistical concepts like

- A. Standard Deviation
- B. Variance and Covariance
- C. Eigen Vectors and Eigen Values

PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analysing data.

The other main advantage of PCA is that once you have found these patterns in the data, and you compress the data, i.e. by reducing the number of dimensions, without much loss of information.

4.2.1 PCA Procedure

- a. We have collected the data of the sample and stored it in a matrix form. For the purpose of PCA, mean was subtracted from the data. Mean values for each dimension were calculated and subtracted from corresponding dimension. This way a data set of zero mean value is created. Then we created covariance matrix of the prepared data set was calculated. Thus if data set has n direction then covariance matrix will be a square matrix of size n .
- b. As Covariance matrix is a square matrix, its Eigen Vector and Eigen Value can be calculated. Eigen Vector is a square matrix of size n . Eigen values is a vertical vector of size $1 \times n$.
- c. Every eigenvector would be a column vector with as many elements as the number of variables in the original dataset. Thus if we had an initial dataset of the size $T \times n$ (recall: rows are the observations, columns represent variables, and therefore we have T observations of n variables), the covariance matrix would be of the size $n \times n$, and each of the eigenvectors will be $n \times 1$. Eigen value clearly indicates that not all of the Eigen Vectors were contributing significantly.
- d. The eigenvalues for each of the eigenvectors represent the amount of variance that the given eigenvector accounts for. We arrange the eigenvectors in decreasing order of the eigenvalues, and pick the top 2, 3 or as many eigenvalues that we are interested in depending upon how much variance we want to capture in our model. If we include all the eigenvectors, then we would have captured all the variance but this would not give us any advantage over our initial data.
- e. Thus Eigen Vectors having higher Eigen Values were selected as Feature Vector. Now as few Eigen Vectors were selected, the data can be transformed to lower dimensional data. Below is the formula to calculate final data.

Final Data = Transpose of Feature Vector Matrix * Transpose of Mean Adjusted Data

4.2.2 How PCA is useful for ratio selection:

Eigen Values shows the contribution of each Eigen Vector in the data set. AS we have seen that with the help of Eigen Values, we can determine most contributing Eigen Vectors i.e. Feature Vector.

The dimension of vector can vary from 1 to n (dimension of original data set). Thus when data set is multiplied with Feature Vector then the resulting matrix is of same dimension as Feature Vector. The original data of n dimension is now transformed over a new m ($n > m$) dimension space. This is how PCA is useful for Ratio Reduction.

We have used PCA in combination with MDA with 22 ratios. PCA Matrix for all the companies for the selected 22 ratios is calculated with the help of methodology discussed.

4.3 Artificial Neural Network (ANN)

Artificial neural networks are non-parametric and flexible tools for estimation and

classification. ANNs are capable of performing complex function mapping with desired accuracy. Neural networks (ANNs) are composed of layers of several computing elements called nodes or neurons. Every node receives a signal called inputs from other nodes and after processing inputs through a transfer function, a transformed signal is sent to other nodes for final result. ANNs are different by network architecture. There is input layer, hidden layers and output layer in a neural net. Every layer can have different number of neurons/nodes. The nodes and layers are built in a feed forward method. A multi-layer feed forward network with an input layer, one hidden layer and output node is shown in the figure below. The three layer feed-forward neural network is commonly used for bankruptcy prediction in previous studies such as Wilson and Sharda (1994), Tam and Kiang (1992), and Wilson and Sharda (1994).

In a statistical model, parameters or weights of an ANN is required to be estimated. The process of discovering these weights is referred as training. The training of neural network is critical for estimation problem.

In the training of neural networks, patterns and examples are introduced to the first or input layer of ANN. The activated values of the input layer nodes are weighted and subsequently accumulated in the hidden layer node. The weighted sum is then transferred by a suitable transfer function in the nodes activation value. Subsequently, it is then treated as an input into the nodes in the final or output layer. Afterwards, an output value gets achieved to match the value desired. The training process of an ANN minimizes the deviation between the neural net output and known targets.

4.3.1 Application of Neural Networks for Bankruptcy Prediction

Neural Networks have been a tool of interest for many business applications including insolvency forecasting/industrial sickness in few decades. ANN models have already been used successfully for many financial problems including bankruptcy prediction Trippi (1993), Zahedi (1996). Many researchers in bankruptcy forecasting including Lacher et al. (1995), Wilson and Sharda (1994), Tam and Kiang (1992), and Wilson and Sharda (1994) report that neural networks produce significantly better prediction accuracy than classical statistical techniques. The model based on ANN constructed for prediction of industrial sickness in this study is feed-forward multi layered back propagation neural network.

For construction of ANN, the data is randomly divided into a training set and a test set which is generally known as in-sample and out-of-sample set. The training set is generally used for training of the neural network whereas the test set is used to evaluate the predictive capability of the model. Neural networks contend with the genetic structures in a streamlined way (Bischof et al., 1992).

In reality, the ANN are internally multivariate mathematical models that use iterative procedures processes to minimize error functions. Artificial neurons, as well as biological ones, are defined to be in state of activation at all times, which can be expressed by a numeric value corresponding to the formula:

$$a = \sum_{i=1}^n w_i x_i \quad (12)$$

Being x_i the value of from each previous neuron activation layer, and w_i the weight assigned to that value. A transfer or output function transforms this value into an output signal that travels through the connections to other neurons of the subsequent levels, eliminating the linearity of the network and limiting values within a certain range.

In this study, a three-layer feed-forward back propagation neural network was used. The structure of the ANN was including 3 layer i.e. input layer, hidden layer and output layer.

In this study, based upon the selection of inputs, 22 ratios were selected as input variables. The neural net had one hidden layer with 22 nodes and output node. There was one output node which will be indicating the J score. The network was run for 10,000 iterations for making predictions. Desai and Joshi (2015).

There are no rules to follow as far as the architecture of the neural net is concerned. The architecture of the neural net would depend upon the forecasting objective. In a neural network, if too complex architecture is used, then the problem of over fitting would harm the forecasting ability. Too simple a network would result in loose estimation and thus would deteriorate the predicting capabilities. The architecture of the neural network for effective forecasting is a process of trial and error. Based upon the complexities of data, the neural network used in the study has three layers as mentioned above. If the results of the training on out of sample data is not effective, there would be a need to increase or decrease the complexity of the neural net but the basics of the feed-forward network with back propagation algorithm would remain the same.

In this study, the functional form is generated by using a multi-layered feed forward artificial neural network. Artificial neural networks (ANNs) are simplified models of the interconnections between cells of the brain. In fact they are defined by Wasserman and Schwartz (1988) as "highly simplified models of the human nervous system, exhibiting abilities such as learning, generalization and abstraction." Hawley, Johnson and Raina (1990) studied that "such models were developed in an attempt to examine the manner in which information is processed by the brain. These models have, in concept, been in existence for many years but the computer hardware requirements of even the most rudimentary systems exceeded existing technology."

The quality of the data has a high impact on the performance and the reliability of the ANN. The neural networks recognize the patterns of the data to a great extent which influence the accurateness of the outcome. The pre-processing of the input variable of the NN enables de-trending of the figures and explain the important relationship to provide appropriate process of learning. During the learning process, the ANN identifies weights for the input variables. A non-linear scaling method is adopted for the improvement of the network's performance.

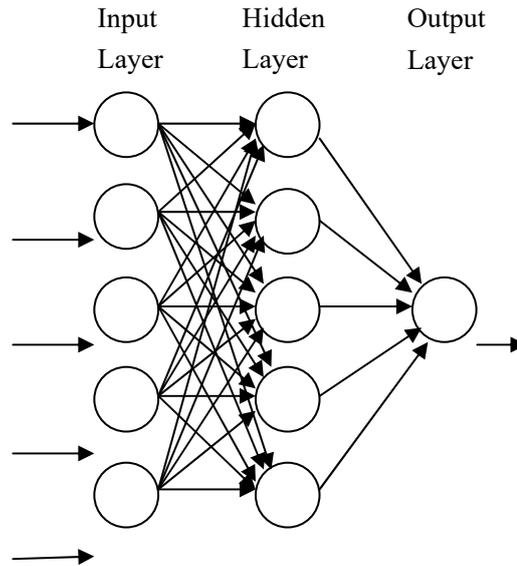


Figure 1. Neural Network Architecture

The figure 1 above represents a feed forward Artificial Neural Network with five input nodes in the input layer, five nodes in the hidden layer and one node in the output layer. There are no rules available on the architecture of an ANN for forecasting of insolvency. The structure of an ANN is developed based on experimentation. High complexity in the architecture can result in over fitting and low complexity can result in loss of learning. For this study a similar three layer ANN with one input layer, one hidden layer and one output layer has been used. The input layer has 22 nodes, hidden layer has 22 nodes and output layer has one output node. This three layer feed forward is commonly used ANN for insolvency prediction and estimation. During the study the neural network was tested with 0, 5, 10, 15 and 22 nodes in the hidden layer, the ANN with 22 nodes in the hidden layer was found to be more suitable in the study.

5. Analysis and Validation of Models

The models are developed on 80 firms split into two categories (solvent/insolvent) of 40 each. Out of the total sample size, we have used a sample of 50 firms (25 firms of each category) as the training sample. Whereas the remaining 30 companies were used as the holdout or validation sample. The firms selected for the training set were based on the weightage of a particular industry in the entire sample. The predictive ability of the models was found to be very high on the validation sample. The following table shows the predictive ability of the models on the entire sample including the training sample as well as validation sample.

The models show that there are 22 financial ratios which have emerged as predictors of industrial sickness out of which two models were developed using MDA i.e. model using 16 ratios and model using 22 ratios. Then using these 22 ratios models were developed using MDA + PCA and ANN. All the models used the training and out-of-sample test for validating the model results.

Table 4. Models for Prediction of Industrial Sickness

Models		Correct Classifications - Solvent Firms	Correct Classifications - Insolvent Firms	Overall Correct Classification
MDA based Model using 16 Ratios	$J = 2.6068 - 3.9099 R_1 + 4.5035 R_2 + 0.1997 R_3 - 12.9819 R_4 + 0.0289 R_5 + 0.1985 R_6 + 0.0033 R_7 - 0.0018 R_8 + 20.6122 R_9 - 3.8964 R_{10} + 7.9591 R_{11} + 0.0305 R_{13} + 0.1488 R_{12} + 0.494 R_{14} + 0.0795 R_{15} - 12.6974 R_{16}$	95%	80%	87.5%
MDA based Model using 22 Ratios	$J = -0.6039 - 5.4072 R_1 + 5.1417 R_2 - 2.692 R_3 - 12.6854 R_4 + 0.4379 R_5 + 0.2299 R_6 + 0.1946 R_7 - 0.0024 R_8 + 19.8018 R_9 - 12.2403 R_{10} + 11.4643 R_{11} + 0.0038 R_{12} - 0.1788 R_{13} + 0.5525 R_{14} + 0.5273 R_{15} - 10.1682 R_{16} + 1.7545 R_{17} + 1.5981 R_{18} - 0.0039 R_{19} + 12.3612 R_{20} + 5.8985 R_{21} + 8.2321 R_{22}$	87.5%	95%	91.25%
MDA+ PCA based Model using 22 Ratios	22X22 Matrix	85%	95%	90%
ANN based model using 22 ratios	Artificial Neural Network Model ANN Algorithm: Back Propagation Structure: 3 Layers (Input, Hidden, Output)	84%	96%	86%

	22 Neurons in input layer 22 Neurons in hidden layer 1 Neuron in output layer (J Score) The network was run for 10,000 iterations for making predictions. Observations used for training: 302 Out of sample prediction was tasted on: 100 observations			
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The present study shows that different models developed using different methodologies deliver different prediction accuracy results and misclassification errors respectively. The previous research works also exhibited different results of prediction accuracy and misclassification errors when different sets of financial ratios were employed.

This study concludes that out of the four proposed models, predictive ability of MDA based model using 22 ratios is found to be highest. MDA based model using 22 ratios shown the predictive accuracy of 91.25% followed by the PCA+MDA model with an accuracy of 90%. The ANN based model is able to predict the industrial sickness in two years advance with the predictive accuracy of 86%.

These models constructed and validated are preferred over the existing empirical models like Altman (1968) and Ohlson (1980). Altman's Z score model and the logit model of Ohlson were estimated on the same sample used in the study and they gave the predictive accuracy of 78% and 81% respectively. Therefore, the comparison of empirical analyses is done on the basis of rejection rates of the same sample and not on the basis of the rejection rates from the literature on different samples.

The results of these models are in line with the previous studies though other studies have considered different sets of financial ratios; Mohamed, Li and Sanda (2001) found leverage ratio and efficiency ratio (total asset turnover) to be significant in explaining bankruptcy during the period 1987 to 1997 (Abdullah, Halim, Ahmad and Rus., 2008) Mine and Hakan (2006) identified EBITDA/total assets as the most important predictor of financial distress in both MDA and Logit models; Sharma and Rao (1976) arrived at a discriminant function using MDA, that comprised of five financial ratios namely, net worth to total assets, debtors turnover, working capital to total assets, retained earnings to total assets and EBIT to total assets. Gupta (1983) by employing Discriminant analysis, found that net worth to short and long term debt and all outside liabilities to tangible assets were useful. Patrick (1932) reported that two significant ratios were Net Worth to Debt and Net Profits to Net Worth.

The present study shows that different models developed using different methodologies deliver different prediction accuracy results and misclassification errors respectively. The previous research works also exhibited different results of prediction accuracy and misclassification errors when different sets of financial ratios were employed; Deakin (1976)

employed MDA with 14 factors and found that the failed firms had 77%, 96%, 94%, 91% and 87% prediction accuracy in the years before failure and non-failed firms showing 82%, 92%, 82%, 67% and 78% in respective years. Ohlson (1980) Logit model was employed with 9 factors, 96% accuracy in both found that when was observed. Aziz, Emanuel and Lawson (1988) found bankrupt firms showing prediction accuracy of 85.7% in 1 79.6% in 3rd year, 81.3% in 4th and 84.8% in 5th used Logit analysis and ear, year prior to sickness whereas non-bankrupt firms showing 98.0%, 83.7%, 77.6%, 79.2% and 76.7% in respective years. Dimitras, Slowinski, Susmaga and Zopounidis (1999) MDA resulting in bankrupt firms with accuracy at 63.2%, 42.1% and 36.8% in the 1st, 2nd and 3rd years prior to sickness and non-bankrupt firms at 68.4%, 63.7% and 73.7% in respective years and Logit model resulting in bankrupt firms with prediction accuracy of 63.2%, 31.6% and 36.8% and non-bankrupt firms at 57.9%, 84.2% and 84.2% in respective years.

6. Implications

Bankruptcy prediction is an interesting and important problem. A better understanding of the causes and prediction accuracy will have tremendous financial and managerial consequences. This study provide bankruptcy prediction models for multiple industries. This study focuses on independent variables which can be used to predict bankruptcy for firms in various industries such as textile, cement, electricals, pharmaceuticals, consumer food etc. The use of these models for bankruptcy prediction had shown several advantages and bankers, credit managers, executives, and investors.

Industrial sickness has become a severe problem requiring a comprehensive redressal rather than inventing quick fixes to revive sick/insolvent firms. The progressive increase in industrial sickness has been causing considerable concern to the Government, Financial Institutions and Banks. This study has a huge commercial impact as these models can be used by the financial institutions and banks in their credit appraisal procedure. The banks and financial institutions can improve the quality of their lending which can help them reduce their non-performing assets. These models will assist the lenders to classify the borrowing units into a potentially solvent or insolvent category. However, it should not be the only means of credit evaluation. Other important non-accounting variables such as the purpose of the loan, maturity of the loan, security involved and deposit status of the applicant should also be considered along with the model score.

This study may also be used for evaluating the repayment behavior of a borrower. This will assist the lenders and enable them to tighten their grip of inspections to force the units to improve their performance.

These models will be able to reduce the locking up of financial resources, wastage of capital assets, loss of production and decrease in employment. This study tries to bridge the gap between theory and practice. These models can be used to check the firm's future health and survival. This study shows a coherent framework consisting of the dynamics of sickness and a forewarning system which can identify the incidence of sickness in different industries so that timely action can be taken. It can also be used for the purpose of teaching various parameters which can lead to industrial sickness or corporate insolvency, how the

intervention can be made which may involve change in management of the firms or funding by other organisations to prevent further sickness. These models can be used to stem further growth of industrial sickness in the country which may influence the quality of life.

The models may be used by the potential investors for screening out undesirable investments. Since the models are of predictive nature, the investors may use it for portfolio selection.

7. Limitations of the Study

A number of limitations of the study and needs for the future research must be noted.

The results of the models should be read with caution as only financial ratios were used as quantitative variables. There may be other qualitative and quantitative variables which can be included. Another limitation of this study is that there are four different models using different techniques which have their advantages and disadvantages. A major limitation of this study is that the prediction models constructed include the use of 22 ratios. Models with such huge number of ratios as inputs make them more complicated. This study includes the sample of listed manufacturing companies in India and the service sector companies, small and medium enterprises are out of the scope of the study which can be considered as the limitation of the study.

Another limitation of this study is the possibility of the model to be extended for general application. We are of the opinion that these models can be generalized to other industries in India but these models may not be generalized for other time periods or other countries. This is a major limitation of this study as we have used a relatively smaller sample and a particular year of defaults.

8. Conclusion

The models which are constructed and validated in the study show that there are 22 financial ratios which have emerged as predictors of industrial sickness out of which two models were developed using MDA i.e. model using 16 ratios and model using 22 ratios. Then using these 22 ratios models were developed using MDA + PCA and ANN.

Beyond all this, ANN based model has shown better results than other models in another sense. Where MDA based models give the score of the year on the basis of which prediction regarding industrial sickness can be made for the next year. Whereas ANN based model gives you the predicted results (score) of the next year on the basis of which the industrial sickness can be predicted for the next 2 years. For example, MDA based model in the present study gives the J score of the year 2014 on the basis of which the sickness can be predicted for the year 2015. On the other side, ANN based model gives you the results/score of the year 2015 on the basis of which the sickness can be predicted for the year 2016. In other words, ANN based model was able to predict the sickness two years in advance as compared to other models which were predicting sickness in one year advance. Thus, ANN model is having more accuracy than other models.

Out of the four proposed models, predictive ability of MDA based model using 22 ratios is found to be highest. The research findings establish the superiority of artificial intelligence

model over discriminant analysis if certain functions and weights are changed and demonstrate the significance of accounting ratios in predicting default.

9. Scope for Further Research

The most imperative area for further research is to extend these models to service sector firms. An attempt can be made to extend the analysis to private limited companies and unincorporated entities where the incidence of failure is more than big corporations.

Another valuable development can be made by including non-financial measures such as operational and technical parameters which may improve the results. A combination of these parameters can be used for early detection of sickness.

Statistical methods have been applied to many areas, but the development of a new algorithm is difficult. SVMs (Support Vector Machines) have powerful generations, but have little explanation ability. Future research is needed to develop a hybrid system integrating various forecasting tools such as the statistical methods and AIs. More works need to be done in prototype development and actual applications need to be empirically tested before the full potential of ANN can be asserted. Further research can be done to check whether employment of PCA with logit can produce better predictive performance. Investigation on bankruptcy prediction models for service industry firms can also be valuable.

References

Abdullah, N. A., Hallim, A., Ahmad, H., & Rus, R. M. (2008). Predicting Corporate Failure of Malaysia's Listed Companies: Comparing Multiple Discriminant Analysis, Logistic and Hazard Model. *International Journal of Finance and Economics*, 15, 201-217.

Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? *Accounting and Business Research*, 37(4), 285-300. <https://doi.org/10.1080/00014788.2007.9663313>

Ahn, H., & Kim, K. (2009). Bankruptcy prediction modeling with hybrid case-based reasoning and genetic algorithms approach. *Applied Soft Computing*, 9(2), 599-607. <https://doi.org/10.1016/j.asoc.2008.08.002>

Alici, Y. (1996). Neural networks in corporate failure prediction: The UK experience, in: A.P.N. Refenes, Y. Abu-Mostafa, J. Moody, A. Weigend (Eds.) (1996), *Neural Networks in Financial Engineering*, World Scientific, Singapore, pp. 393-406.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(3), 589-609. <https://doi.org/10.1111/j.1540-6261.1968.tb00843.x>

Altman, E. (2002 a). *Bankruptcy, Credit Risk, and High Yield Junk Bonds*, Massachusetts: Blackwell Publishers.

Altman, E. (2002 b). *Corporate Distress Prediction Models in a Turbulent Economic and Basel II Environment*, Risk Books, London. Retrieved from

<http://pages.stern.nyu.edu/~ealtman/Corp-Distress.pdf> as on 21 October 1994

Altman, E., Hartzell J., & Peck M. (1995). *Emerging Markets Corporate Bonds: A Scoring System*. Salomon Brothers Inc., New York, 1995.

Altman, E., Haldeman R., & Narayanan P. (1977). ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance*, June.

Altman, E.I., & Narayanan, P. (1997). An international survey of business failure classification models. *Financial Markets, Institutions and Instruments*, 6(2), 1-57. <https://doi.org/10.1111/1468-0416.00010>

Asquith, P., Gertner, R., & Scharfstein, D. (1994). Anatomy of financial distress: an examination of junk bond issuers. *Quarterly Journal of Economics*, 625-658. <https://doi.org/10.2307/2118416>

Avcı, E., & Turkoglu, I. (2009). An intelligent diagnosis system based on principle component analysis and ANFIS for the heart valve diseases. *Expert Systems with Applications*, 36(2), 2873-2878. <https://doi.org/10.1016/j.eswa.2008.01.030>

Aziz, A., Emanuel, D.C., & Lawson, G.H. (1988). Bankruptcy Prediction - An Investigation of Cash Flow Based Models. *Journal of Management Studies*, 25(5), 419-435. <https://doi.org/10.1111/j.1467-6486.1988.tb00708.x>

Back, B., Laitinen, T., & Sere, K. (1996), Neural networks and genetic algorithms for bankruptcy predictions. *Expert Systems with Applications*, 11(4), 407-413. [https://doi.org/10.1016/S0957-4174\(96\)00055-3](https://doi.org/10.1016/S0957-4174(96)00055-3)

Beaver, W. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, 4, 71-111. <https://doi.org/10.2307/2490171>

Beaver, W. (1968). Alternative accounting measures as predictor of failure. *The Accounting Review*, 43, January, 113-122.

Belsley, D. A., E. Kuh, & R. E. Welsch. (1980). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York: Wiley <https://doi.org/10.1002/0471725153>

Bischof, H., Schneider, W., & Pinz, A.J. (1992). Multispectral classification of Landsat images using neural networks. *IEEE Transactions on Geoscience and Remote Sensing*, 30(3), 482-490. <https://doi.org/10.1109/36.142926>

Boritz, E., Kennedy, D., & Albuquerque, A. (1995). Predicting corporate failure using a neural network approach. *International Journal of Intelligent Systems in Accounting, Finance and Management*, 4(2), 95-112.

Chauhan, N., Ravi, V., & Chandra, D. K. (2009). Differential evolution trained wavelet neural networks: Application to bankruptcy prediction in banks. *Expert Systems with Applications*, 36(4), 7659-7665. <https://doi.org/10.1016/j.eswa.2008.09.019>

- Cheng, C. B., Chen, C. L., & Fu, C. J. (2006). Financial distress prediction by a radial basis function network with logit analysis learning. *Computers & Mathematics with Applications*, 51(3-4), 579-588. <https://doi.org/10.1016/j.camwa.2005.07.016>
- Cho, S., Hong, H., & Ha, B.-C. (2010). A hybrid approach based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance; for bankruptcy prediction. *Expert Systems with Applications*, 37(4), 3482-3488. <https://doi.org/10.1016/j.eswa.2009.10.040>
- Cho, S., Kim, J., & Bae, J. K. (2009). An integrative model with subject weight based on neural network learning for bankruptcy prediction. *Expert Systems with Applications*, 36(1), 403-410. <https://doi.org/10.1016/j.eswa.2007.09.060>
- Cybenko G. (1989). Approximation by super positions of a sigmoid function. *Mathematical Control Signals Systems*, 2, 303-314. <https://doi.org/10.1007/BF02551274>
- Datta D. K. (2013). Industrial Sickness in India - An Empirical Analysis. *IIMB Management Review*, 25(2), 104-114. <https://doi.org/10.1016/j.iimb.2013.02.003>
- Deakin, E. B. (1976). Distribution of Financial Accounting Ratios: Some Empirical Evidence. *The Accounting Review*, April, pp. 18-28.
- Desai J., & Joshi N. (2015). Application of Artificial Intelligence for Forecasting Industrial Sickness. *International Journal of Engineering and Technical Research (IJETR)*, 3(12). ISSN: 2321-0869 (O) 2454-4698 (P), December.
- Dimitras, A., Slowinski, R., Susmaga, R., & Zopounidis, C. (1999). Business Failure Prediction Using Rough Sets. *European Journal of Operational Research*, 263-280. [https://doi.org/10.1016/S0377-2217\(98\)00255-0](https://doi.org/10.1016/S0377-2217(98)00255-0)
- Etemadi, H., Rostamy, A. A. A., & Dehkordi, H. F. (2009). A genetic programming model for bankruptcy prediction: Empirical evidence from Iran. *Expert Systems with Applications*, 36(2), 3199-3207. Part 2. <https://doi.org/10.1016/j.eswa.2008.01.012>
- Gentry, J. A., Newbold, P., & Whitford, D. T. (1987) Funds flow components, financial ratios and bankruptcy. *Journal of Business Finance and Accounting*, 14(4), 595-606. <https://doi.org/10.1111/j.1468-5957.1987.tb00114.x>
- Gnanadesikan, R., & J. R. Kettenring. 1972. Robust estimates, residuals, and outlier detection with multiresponse data. *Biometrics*, 28(March), 81-124. <https://doi.org/10.2307/2528963>
- Grunert, J., Norden, L., & Weber, M. (2005). The role of non-financial factors in internal credit ratings. *Journal of Banking and Finance*, 29, 509-531. <https://doi.org/10.1016/j.jbankfin.2004.05.017>
- Gupta L. C., (1983). *Financial Ratios for Monitoring Corporate Sickness*, Oxford University Press. New Delhi.
- Gupta V. (2014). An Empirical Analysis of Default Risk for Listed Companies in India: A Comparison of Two Prediction Models. *International Journal of Business and Management*,

9(9). ISSN 1833-3850 E-ISSN 1833-8119, Published by Canadian Center of Science and Education.

Hair, J. F., et al. (2006). *Multivariate data analysis*, Upper Saddle River, NJ: Pearson Prentice Hall.

Hardle, W., Lee, Y., Schafer, D., & Yeh, Y. (2009). Variable selection and oversampling in the use of smooth support vector machines for predicting the default risk of companies. *Journal of Forecasting*, 28(6), 512-534. <https://doi.org/10.1002/for.1109>

Hawley, D.D., Johnson J. D., & Raina D. (1990). Artificial Neural Systems: A New Tool for Financial Decision-Making. *Financial Analysis Journal*, Nov/Dec, 63-72. <https://doi.org/10.2469/faj.v46.n6.63>

Haykin S. (1999). *Neural Networks: A Comprehensive Foundation*, 2nd Edition, Prentice Hall International.

Hornik K. (1991), Approximation Capabilities of Multi-layer Feed Forward Network. *Neural Networks*, 4, 251-257. [https://doi.org/10.1016/0893-6080\(91\)90009-T](https://doi.org/10.1016/0893-6080(91)90009-T)

Hua, Z.-S., Wang, Y., Xu, X.-Y., Zhang, B., & Liang, L. (2007). Predicting corporate financial distress based on integration of support vector machine and logistic regression. *Expert Systems with Applications*, 33, 434-440. <https://doi.org/10.1016/j.eswa.2006.05.006>

Izan, H. (1984). Corporate Distress in Australia. *Journal of Banking and Finance*, 8, 303. [https://doi.org/10.1016/0378-4266\(84\)90010-4](https://doi.org/10.1016/0378-4266(84)90010-4)

Jo, H., Han, I., & Lee, H. (1997). Bankruptcy prediction using case-based reasoning, neural network and discriminant analysis for bankruptcy prediction. *Expert Systems with Applications*, 13(2), 97-108. [https://doi.org/10.1016/S0957-4174\(97\)00011-0](https://doi.org/10.1016/S0957-4174(97)00011-0)

Kim, M., & Kang, D. (2010). Ensemble with neural networks for bankruptcy prediction. *Expert Systems with Applications*, 37(4), 3373-3379. <https://doi.org/10.1016/j.eswa.2009.10.012>

Kumar, R. G., & Kumar, K. (2012). A comparison of bankruptcy models. *International Journal of Marketing, Financial Services and Management Research*, 1(4).

Lacher R., Coats P., Sharma S., & Fant L. (1995). A neural network for classifying the financial health of a firm. *European Journal of Operations Research*, 85, 53-65. [https://doi.org/10.1016/0377-2217\(93\)E0274-2](https://doi.org/10.1016/0377-2217(93)E0274-2)

Laitinen, E. (1991). Financial Ratios and different failure Processes. *Journal of Business Finance & Accounting*, 18(5), 649-657. <https://doi.org/10.1111/j.1468-5957.1991.tb00231.x>

Lee, S., & Choi, W. S. (2013). A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis. *Expert Systems with Applications*, 40(8), 2941-2946. <https://doi.org/10.1016/j.eswa.2012.12.009>

Lennox, C. (1999). Identifying failing companies: A re-evaluation of the logit, probit and

- MDA approaches. *Journal of Economics and Business*, 51(4), 347-364. 203. [https://doi.org/10.1016/S0148-6195\(99\)00009-0](https://doi.org/10.1016/S0148-6195(99)00009-0)
- Lensberg, T., Eilifsen, A., & McKee, T. E. (2006). Bankruptcy theory development and classification via genetic programming. *European Journal of Operational Research*, 169, 677-697. <https://doi.org/10.1016/j.ejor.2004.06.013>
- Li, H., & Sun, J. (2010). Forecasting business failure in China using case-based reasoning with hybrid case representation. *Journal of Forecasting*, 29(5), 486-501.
- Li, H., & Sun, J. (2011). Empirical research of hybridizing principal component analysis with multivariate discriminant analysis and logistic regression for business failure prediction. *Expert Systems with Applications*, 38(5), 6244-6253. <https://doi.org/10.1016/j.eswa.2010.11.043>
- Li, H., & Sun, J. (2011). On performance of case-based reasoning in Chinese business failure prediction from sensitivity, specificity, positive and negative values. *Applied Soft Computing*, 11(1), 460-467. <https://doi.org/10.1016/j.asoc.2009.12.005>
- Li, H., Adeli, H., Sun, J., & Han, J. (2011). Hybridizing principles of TOPSIS with case based reasoning for business failure prediction. *Computers & Operations Research*, 38(2), 409-419. <https://doi.org/10.1016/j.cor.2010.06.008>
- Li, H., Sun, J., & Sun, B.-L. (2009). Financial distress prediction based on OR-CBR in the principle of k-nearest neighbors. *Expert Systems with Applications*, 39(1), 643-659. <https://doi.org/10.1016/j.eswa.2007.09.038>
- Libby, R. (1975). Accounting Ratios and the Prediction of Failure; Some Behavioral Evidence. *Journal of Accounting Research*, 13(1), 150-161. <https://doi.org/10.2307/2490653>
- Lin, F.-Y., & McClean, S. (2001). A data mining approach to the prediction of corporate failure. *Knowledge-Based Systems*, 14, 189-195. [https://doi.org/10.1016/S0950-7051\(01\)00096-X](https://doi.org/10.1016/S0950-7051(01)00096-X)
- Lincoln, M. (1984). An Empirical Study of the Usefulness of Accounting Ratios to Describe Levels of Insolvency Risk. *Journal of Banking and Finance*, 7, 321. [https://doi.org/10.1016/0378-4266\(84\)90011-6](https://doi.org/10.1016/0378-4266(84)90011-6)
- Mahalakshmi A. (2013). Industrial Sickness in Indian Corporate Sector: Discriminators, Predictors and Development of Prediction Models, Ph. D. Thesis Submitted to Bharathiar University, May - 2013.
- Min, J.-H., & Lee, Y.-C. (2005). Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. *Expert Systems with Applications*, 28, 603-614. <https://doi.org/10.1016/j.eswa.2004.12.008>
- Min, S.-H., Lee, J., & Han, I. (2006). Hybrid genetic algorithms and support vector machines for bankruptcy prediction. *Expert Systems with Applications*, 31(3), 652-660. <https://doi.org/10.1016/j.eswa.2005.09.070>

- Mine U., & Hakan A., (2006). Prediction of corporate financial distress in an emerging market: the case of Turkey. *Cross Cultural Management: An International Journal*, 13(4), page 277-295. <https://doi.org/10.1108/13527600610713396>
- Mohamed S, Li AJ, & Sanda A. U. (2001). Predicting corporate failure in Malaysia: An application of the Logit Model to financial ratio analysis. *Asian Academy of Management Journal*, 6(1), 99-118.
- Nam, J., & Jinn T. (2000). Bankruptcy prediction: Evidence from Korean listed companies during the IMF crisis. *Journal of International Financial Management and Accounting*, 11(3), 178-197. <https://doi.org/10.1111/1467-646X.00061>
- Odom, M., & Sharda, R. (1990). A neural networks model for bankruptcy prediction. *Proceedings of the IEEE International Conference on Neural Network*, 2, 163-168.
- Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109-131. <https://doi.org/10.2307/2490395>
- Patrick, P. F. (1932). A Comparison of the Ratios of successful Industrial Enterprises with That of Distressed Companies. *Journal of Accounting Research*, 727-731.
- Pendharkar, P. C. (2005). A threshold-varying artificial neural network approach for classification and its application to bankruptcy prediction problem. *Computers & Operations Research*, 32, 2561-2582. <https://doi.org/10.1016/j.cor.2004.06.023>
- Polat, K., & Günes, S. (2008). Principles component analysis, fuzzy weighting preprocessing and artificial immune recognition system based diagnostic system for diagnosis of lung cancer. *Expert Systems with Applications*, 34(1), 214-221. <https://doi.org/10.1016/j.eswa.2006.10.011> <https://doi.org/10.1016/j.eswa.2006.09.001>
- Ravisankar, P., & Ravi, V. (2010). Financial distress prediction in banks using Group Method of Data Handling neural network, counter propagation neural network and fuzzy ARTMAP. *Knowledge-Based Systems*, 23(8), 823-831. <https://doi.org/10.1016/j.knosys.2010.05.007>
- Rekha Pai G A, R Annapoorani, & G A Vijayalakshmi Pai, (2006) A Principal Component Analysis-Multiple Discriminant Analysis model for prediction of corporate failure in India. *Finance India*, XX(4), 1413-1428, Dec.
- Sahoo, P. K., Mishra, K. C., & Soothpathy, M. (1996). Financial Ratios as the Forewarning Indicators of Corporate Health. *Finance India*, 10(4), 955-965.
- Serrano-Cinca, C. (1997). Feed forward Neural Networks in the Classification of Financial Information. *European Journal of Finance*, 3(3), 183-202. <https://doi.org/10.1080/135184797337426>
- Sharma L.V.L.N., & Rao G.B. (1976), 'Financial Ratios as predictors of Failure: A Multivariate Approach. *Indian Manager*, 7(2), April - June, 1976 175-189.
- Shaw, P. (2003). *Multivariate statistics for the environmental sciences*. Hodder-Arnold.

- Shumway, T. (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *Journal of Business*, 74(1), 101-24. <https://doi.org/10.1086/209665>
- Srivastava, S S., & Yadav, R A (1986). *Management and Monitoring of Industrial Sickness*, Concept Publishing House, New Delhi.
- Sun, J., & Li, H. (2008a). Data mining method for listed companies' financial distress prediction. *Knowledge-Based Systems*, 21(1), 1-5. <https://doi.org/10.1016/j.knosys.2006.11.003>
- Sun, J., & Li, H. (2008b). Listed companies' financial distress prediction based on weighted majority voting combination of multiple classifiers. *Expert Systems with Applications*, 35(3), 818-827. <https://doi.org/10.1016/j.eswa.2007.07.045>
- Taffler, R. J. (1984). Empirical models for the monitoring of UK corporations. *Journal of Banking and Finance*, 8(2), 199-227. [https://doi.org/10.1016/0378-4266\(84\)90004-9](https://doi.org/10.1016/0378-4266(84)90004-9)
- Tam K. Y., & Kiang M. Y. (1992), Managerial applications of neural networks: The case of bank failure predictions. *Management Science*, 38(7), 926-947. <https://doi.org/10.1287/mnsc.38.7.926>
- Trippi R., & Turban E. (1993). *Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance*, Probus, Chicago, IL, 159-176.
- Tseng, F., & Hu, Y. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications*, 37(3), 1846-1853. <https://doi.org/10.1016/j.eswa.2009.07.081>
- Wang, Z. (2004). Financial Ratio Selection for default-Rating Modelling: A Model-Free Approach and Its Empirical Performance. *Journal of Applied Finance*.
- Wasserman, P. O. and Schwartz, T. (1988) "Neural Networks - Part II". *IEEE Expert*, 3(1), 10-15. <https://doi.org/10.1109/64.2091>
- West, D., Dellana, S., & Qian, J. (2005). Neural network ensemble strategies for financial decision applications. *Computers & Operations Research*, 32, 2543-2559. <https://doi.org/10.1016/j.cor.2004.03.017>
- Wilson, R., & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, 11(5), 545-557 [https://doi.org/10.1016/0167-9236\(94\)90024-8](https://doi.org/10.1016/0167-9236(94)90024-8)
- Yadav R. A. (1986). *Financial ratios and the prediction of corporate failure*, Concept Publishing Company, New Delhi.
- Yang, Z., You, W., & Guoli Ji, G. (2011). Using partial least squares and support vector machines for bankruptcy prediction. *Expert Systems with Applications*, 38(7), 8336-8342. <https://doi.org/10.1016/j.eswa.2011.01.021>
- Zahedi, F. (1996) A meta-analysis of Financial application of neural networks. *International Journal of Computational Intelligence and Organizations*, 1(3), 164-178.

Zmijewski, M. E. (1984). Methodological Issues Related to Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, 22, 59-82.
<https://doi.org/10.2307/2490859>