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FORECASTING CREDIT RATINGS USING AN ANN AND STATISTICAL TECHNIQUES

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In a liberal environment the conceptual importance of credit rating has increased significantly. The objective of this study is to explore and find out the effect of the financial performance data of a firm relative to the credit rating of a debt issue of that firm. The study also proposes to capture the relationship, if any, between financial performance data and credit rating given by experts in an appropriate model.

Financial data relevant to debt issue ratings are obtained from the publications of a premier credit rating agency in India. Data analysis involved the building of a model using conventional multiple linear discriminant analysis and Artificial Neural Network Systems. Artificial Neural Networks (ANN) model was found to be superior to the discriminant analysis model. The ANN model can be used to increase speed and efficiency of the rating process in practical applications. In addition, if experts provide better-input data, it can be relied upon to provide an automatic rating to a significant extent.

Keywords: *Credit Rating, Rating Methodology, Discriminant Analysis, Artificial Neural Network, Experts System.*

I. INTRODUCTION

In the present day liberalized environment of many developing countries, the issue of Credit Rating has become a crucial aspect not only for issuers and subscribers of a debt, but also for investors (ranging from individual investors to foreign institutional investors). Credit rating, which is the indicator provided by an autonomous professional agency, reflects the willingness and the ability of the issuers of debt to honor the terms of the client's obligations in terms of repayment of interest and principal payments.

To evaluate a bond's potential, rating agencies rely upon a committee analysis of various aspects of the issuing company such as the issuer's ability to repay, willingness to repay and protective provisions for an issue. It is not known what model, if any, is used for analyzing various issues. It is almost impossible to capture all relevant information used by expert(s) to arrive at a specific rating by quantitative

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analysis. Subjective evaluation of qualitative information forms significant, if not only part, of the analysis.

This is the main reason why conventional analysis techniques yield very poor results when used for the prediction of ratings. It is possible to develop rule-based expert systems to predict ratings but usually expert information is confidential.

Usually past performance of a firm is reflected in its current financial information and is not necessarily an indicator of future performance. Nevertheless, financial figures may indicate creditworthiness of an on-going firm because of their significant influence on future performance. In addition, they usually reflect a host of subjective data like management effectiveness, competitive position of firm, customer relations, employee morale etc. Subjective and qualitative information used by experts in the rating a debt obligation of a company may also be reflected by financial figures.

The objective of the study is to verify to whether a relationship exists between financial information of a company and the ratings on debt obligations awarded by experts. Assuming the existence of such a relationship, the study proposes to use Artificial Neural Networks, which have a proven ability to capture hidden relationships between the dependent variable, and a set of independent variables and compare the classification and prediction results with results of conventional discriminant analysis.

The practical utility of the study is in the fact that if a significant relationship is found with the help of an Artificial Neural Network, the same can be used as a benchmark from which expert/s can continue his/her analysis. This will considerably reduce the time and efforts of experts because experts can delegate routine analysis to the Network model and concentrate on qualitative and subjective factors.

BACKGROUND – CREDIT RATINGS

Brief History

The concept of a credit rating has its origin in the U.S.A. In 1860, H.V.Poor, started publishing financial statistics of railroad companies to attract public investments. In 1909, J. Moody, the founder of Moody’s Investors services, further refined the method by using alphabetical symbols in rating the railroad bonds. The system of rating bonds became institutionalized in the United States following the great depression in the late 1930’s. In recent years virtually 100 percent of all commercial paper volume and 99 percent of corporate bond volume is rated by various credit rating agencies in the United States. Today the credit rating agencies have been established in most of the countries to serve the needs of the investors and the corporate borrowers.

Concept

As the number of companies borrowing directly from the capital market increases, and as the economic environment becomes more and more competitive, demanding investors find that neither a borrowers’ financial status nor their brand image constitute a sufficient assurance of timely payment of interest and principal. Investors increasingly feel the need for an independent and creditable credit rating agency,

which judges impartially the credit quality of debt obligations of different companies and assists private/corporate investors and institutional investors in making investment decisions.
In order to understand the concept of credit rating it is desirable to know the definitions given by some important credit agencies.

- Standard and Poors – A Standard and Poors corporate or municipal debt rating is a current assessment of the credit worthiness of an obliger with respect to a specific obligation.
- Moody's Investor Service – Ratings are designed exclusively for the purpose of grading bonds according to their investment qualities.
- Australian ratings – A corporate rating provides lenders with a simple system of gradation by which the relative capacities of companies to make timely payment of interest and principal on a particular type of debt can be noted.
- CRISIL (Credit Rating Information Services of India) Ltd. – CRISIL is India's premier rating agency. It has an association with Standard and Poors to provide credit ratings. The CRISIL rating symbols indicate in a summarized manner, CRISIL's current opinion as to the relative safety of timely payment of interest and principal on a debenture, preference share, fixed deposit or short term instruments. It is to be noted that CRISIL only rates debt obligations of selective companies. CRISIL uses an alphabetical code starting from AAA (highest safety - high investment grade) to D (default - speculative grade). For details and definition of each symbol, please refer to Appendix 2.

  Thus, a credit rating is not a general evaluation of the issuing organization. It reflects the relative probability of timely payment of principal and interest by the borrowing company. The credit rating is not a one-time evaluation of credit risk of a security. The rating company may change the rating considering the changes periodically. The crucial point here is that Credit rating is not intended to serve as a recommendation but it is an objective evaluation and source of information.

Various Types

Credit ratings are of different types, depending upon the requirements of the rater and the rated. The following are indicative of the common types of credit rating:

1. Bond rating: Rating the bonds or debt securities issued by a company, Governmental or quasi-Governmental body is called a bond rating. This occupies the major business of credit rating bond agencies.
2. Rating of Short term Instruments: securities with an original maturity of upto one year.
3. Commercial Paper rating: It is mandatory on the part of a corporate body to obtain the rating of an approved credit rating agency to issue commercial paper. In U.S.A 100 per cent of commercial paper volume is rated. In India Pl (plus) rating is prescribed for issue of commercial paper by corporate bodies.
4. Rating the Borrowers: This includes rating a borrower to whom a loan/ credit facility may be sanctioned.
5. Sovereign/ country Rating.

Benefits of Credit Rating

The benefits to various parties concerned with credit rating are listed below:

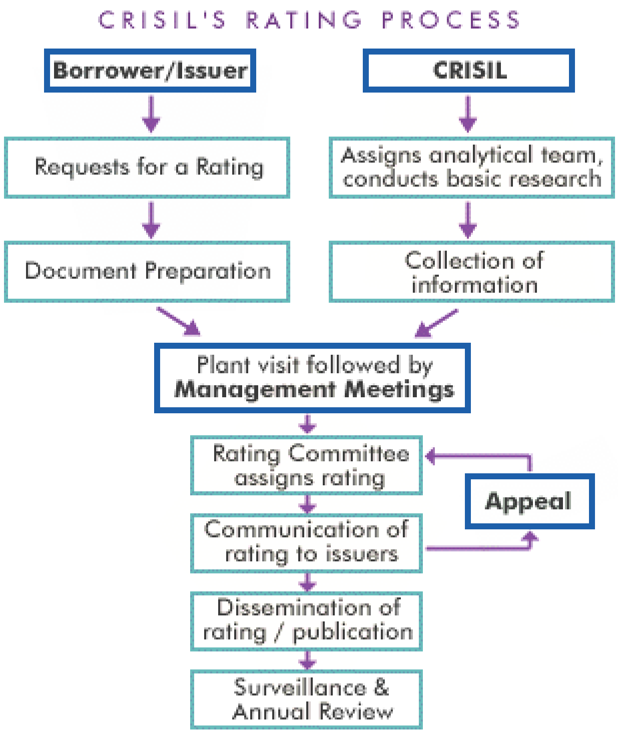
1. It enables the investors to get superior information at low cost and take a calculated risk.
2. It encourages the common man to invest his savings in corporate securities and get high returns.
3. It facilitates companies with good rating to enter the market confidently and raise funds at cheaper rates.
4. It can be used as a tool to improve the brand image of company.
5. Fair and good ratings motivate and sustain public investment in corporate sector, thus fuelling economic growth.
6. It facilitates formulation of public policy guidelines on institutional investments.
7. Credit rating system plays a vital role in investor protection without casting burden for that responsibility on the Government by encouraging discipline among the corporate borrowers.

CRISIL

The Industrial Credit and Investment Corporation of India Ltd. (ICICI), Unit Trust of India and others including several foreign banks in 1988 floated the Credit Rating Information Service of India Limited (CRISIL). Crisil's principal objective is to rate rupee denominated obligations of Indian companies. ICRA (Information and Credit Rating Agency of India), another credit rating agency, was started in 1991 and the youngest of the lot is CARE (Credit Analysis and Research Ltd). It is expected that competition will make rating agencies more effective from both investor and company points of view.

RATING METHODOLOGY

The credit ratings are based on the current information provided to the agency by the company or obtained from the agency from sources it considers reliable. The process of Rating starts with the issue of the Rating request by the issuer and the signing of the Rating agreement. CRISIL employs a multi-layered decision making process in assigning a rating. It assigns a team of at least two analysts who interact with the company's management.



CRISIL commences a rating exercise at the request of a company. This rating, however, applies to a particular debt obligation of the company and is not a general-purpose evaluation of the company. The methodology covers the assessment of 'Business Risks' and 'Financial Risks' associated with the issuer/borrowing entity. CRISIL assigns ratings after assessing all factors that could affect the creditworthiness of the borrowing entity. The ratings are based on current information provided to CRISIL by the borrowing company, or facts obtained by CRISIL from sources it considers reliable. In evaluating and monitoring ratings, CRISIL employs both qualitative and quantitative criteria in accordance with the industry practice.

The rating methodology involves an analysis of the past performance of the company and an assessment of its future prospects. The key factors considered are Business Analysis, Financial Analysis, and Management Evaluation. Details of the methodology can be seen at http://www.crisil.com.

BUSINESS ANALYSIS

- Industry Risk: Nature and basis of competition, key success factors, and demand supply position, structure of industry, cyclical/seasonal factors, Government policies etc.
- Market position of the issuing entity within the industry: Market share, competitive advantages, selling and distribution arrangements, product and customer diversity, etc.
- Operating efficiency of the borrowing entity: Location advantages, labour relationships, cost structure, technological advantages and manufacturing efficiency as compared to competitors etc.

- Legal position: Terms of the issue document/ prospectus, trustees and their responsibilities, systems for timely payment and for protection against fraud/ forgery etc.

FINANCIAL ANALYSIS

- Accounting Quality: Overstatement/ understatement of profits, auditors qualifications, method of income recognition, inventory valuation and depreciation policies, off Balance Sheet liabilities etc.
- Earnings protection: Sources of future earnings growth, profitability ratios, and earnings in relation to fixed income charges etc.
- Adequacy of cash flows: in relation to debt and working capital needs, stability of cash flows, capital spending flexibility, working capital management etc.
- Financial flexibility: alternative financing plans in times of stress, ability to raise funds, asset deployment potential, etc.
- Interest and Tax sensitivity: exposure to interest rate changes, tax law changes, and hedge against interest rates etc.

MANAGEMENT EVALUATION

- Track record of the management: planning and control systems, depth of managerial talent, succession plans.
- Evaluation of capacity to overcome adverse situations.
- Goals, philosophy, and strategies.

II. ARTIFICIAL NEURAL NETWORKS (ANNS)

ANN systems are based on the present understanding of human neuro physiology. Human information processing takes place through the interaction of many billions of neurons, each sending excitatory or inhibitory signals to other neurons (including, in some cases, back to themselves). A typical neuron in a human brain contains a nucleus, an axon, and one or many more dendrites. A nucleus receives signals from the other neurons through ramified dendrites, which collects the input signal and transforms it. A single axon then transmits the transformed signal to other neurons usually by the propagation of an 'action potential'. These signals pass through junctions called synapses, by varying the strength of which, the human brain stores knowledge and also transforms signals into specific outputs.

In order to implement such human information processing in an artificial system, the basic model of ANN techniques consist of computational units called processing elements (PEs) which emulate the function of a nucleus in a human brain. The unit receives a weighted sum of all its inputs and computes its own output value by a transformation or output function. The output is then propagated to many other units via connections between units. Receiving units repeat the identical process. In general, the output function is either a linear function or a threshold function in which a unit becomes active. It comes active when its net input exceeds the threshold limit or some other function. Computational units in ANNs are hierarchically structured layers. Depending upon the layer in which a unit resides, the unit is called the input, a hidden, or an output unit. An input unit (output unit) is smaller to independent (dependant) unit in statistical techniques. A hidden unit is used to augment the input data in order to support any required function from input to output. It captures the underlying interrelationships between output and input.

Computational units in an ANN model are connected by links with variable weights, which represent synapses in a biological model and coefficients in a statistical model. A learning algorithm to represent a function from input to output computes a set of connection weights in the network. The processing of computing appropriate weights is called learning or training. The process of computing weights is similar to parameter estimation in regression analysis.

There are many different learning algorithms that work with different types of output functions. The most commonly used algorithm is called Back Propagation. This algorithm is a non-linear model, which is distribution free. The algorithm suggests a way of modifying weights to represent a function from output to input. As a basic rule, it uses the calculated difference of an error (between actual and expected output) to adjust the weights so as to minimize the total error. Weight changes in a trial run are proportional to error epoch proportion. A minimum tolerable level of error is used to stop the iterations or, alternatively, a fixed number of iterations are used.

- ANN systems have better generalization abilities. Learning capability is both efficient and effective.
- They can handle ill structured data and noise more successfully than expert systems.

However, the explanation power of ANN systems is poor compared to that of expert systems.

ANN systems can be used to assist actively in a number of problems faced in the operations research area and statistical like:

- Prediction/ estimation (curve fittings, forecasting etc)
- Pattern recognition (classification, Discrimination analysis and diagnosis)
- Clustering (grouping without a prior knowledge of classes)
- Optimization (the solution of linear and non linear mathematical programming model involving continuous and/or discrete variables)

Pattern recognition related decision problems suit artificial neural networks more than to statistical techniques primarily because of the complex nature of problems, which are not well understood mathematically and involve subjectivity. In addition, such problems have qualitative and noise data. Even if the values of every input features are not known, a trained neural network will produce a response.

In the finance area, ANNs are applied with significant success in the area of stock price predictions, portfolio selection and management and credit rating analyses. Kumar and Ganesalingam (2000) used ANN to predict financial distress. Chandrasekhar and Vaikunthnath (1994) used ANN for predicting Bond Rating. Haynes and Tan (1993) used an ANN model to predict the selling price of houses. Tan

& Dihardjo (2001) used ANN to develop an early warning predictor for credit union financial distress and Luther (1998) used ANN to predict the outcome of chapter 11 Bankruptcy.

III. RESEARCH METHODOLOGY

Data Collection

Rating Reports Published in CRISIL rating scan issues of May 00, June 00, July 00 and Sept 00 are used in this study. Either a Debenture issue (both Convertible and Non-convertible), Short Term instrument or fixed deposit rating is used for rating various classes. Fourteen financial statistics as given by the experts of CRISIL, extracted along with the concomitant rating for each debenture issue/fixed deposit/short term have been taken for 76 companies. These ratios are:

1. Net Sales (NETSALES)
2. Operating Income (OPERINCO)
3. Operating Profit before Depreciation, Interest and Tax (OPBDIT)
4. Profit after Tax (PAT)
5. Equity Share Capital (ECAPITAL)
6. Tangible Networth (NETWORTH)
7. OPBDIT/Operating Income (OPBOPI)
8. PAT/Operating Income (PATOI)
9. PBIT/(Total Debt + Tangible Networth) - (PBITTDTN)
10. OPBDIT/Interest and Finance Charges (OBBDITFI)
11. PBDIT/ Interest and Finance Charges (PBDITITFI)
12. Net Cash Accruals/Total Debt (NETTOTA)
13. Total Debt/Tangible Networth (DEBTTNET)
14. Current Ratio (Current Assets/Current Liabilities) – (CURRATIO)

Majority of ratings falls in grades of AA, A, BBB, BB for debenture ratings, FAA and FA for fixed deposit ratings and P1+ or P1 for short-term instruments. See Appendix 1 for a full listing of the companies and their assigned rating.

Scaling of Data for Input purposes

For both the ANN and conventional discriminant analysis techniques the dependant variable, i.e. rating, is scaled on a 5 point numeric scale, and independent variables are used in their original form. Ratings on companies which offer all three types of debt instruments have been taken in the following hierarchy – debenture rating, fixed deposit rating and short term instrument rating. See Appendix 3 for a complete listing of the scale used.

DATA ANALYSIS TECHNIQUES

As mentioned before two techniques were used for analysis purposes:

Artificial Neural Network (ANN) Model

Two commonly used models in neural networks are Back Propagation and Vector Quantization. Back propagation types of models are mostly suitable for applications like forecasting and extracting the trend/cyclical patterns in large databases. Vector quantization techniques basically try to partition the space represented by a group of vectors into a predefined number of prototypes. In our case, the prototypes are nothing but the rating of financial instruments. The phases that are involved in solving this type of problem are the training phase and the classification phase. During the training phase the input vector along with the known classification are cycled through the network repeatedly and in this process the network learns the mapping relationship between the input vector attributes and the class associated with it. This relationship is stored in the form of weights. During the classification phase, it uses these weights to arrive at the classification of an input vector. The algorithm of the learning vector quantization can be summarized as follows:

Step 1: Start off with an initial set of prototype vectors for each class. These can be randomly selected or they can be the first few sample vectors themselves. For example, if we have N vectors to be classified into K classes and each vector has P attributes to start with, we can select first K vectors of N as prototype vectors or one can select K random vectors as prototypes.

Step 2: Compute the Euclidian distance between a sample vector X to each of the K prototypes.

Step 3: Assign X to that prototype class for which the distance is smallest.

Step 4: Now X may be classified into correct class or X may not be classified to the correct class. During training phase, the correct class of X is known. Depending on the first or second outcomes the prototype vector is moved closer or away from X by a small amount α or ß. The process is repeated for every vector. This forms one cycle this training set data. This is cycle is repeated until the network stabilizes.

This basic algorithm is also known as the Kohonen form of learning. This has some limitations. Subsequently certain extensions have been done to overcome some of the limitations. One such rule is known as extended learning vector quantization where in several conditions are verified before the prototype vector is moved.

Step 5: For a given sample vector X identify two prototype vectors which have the nearest Euclidian distance.

Step 6: Update the weight vector only if the following conditions are satisfied OR Sample X and the nearest prototype belong to different class OR Sample X and the next nearest prototype belong to same class OR Sample X lies inside a predefined window centered on mid point of two prototypes. During updating, second prototype is moved a small distance (α) towards X and the first prototype is moved a small distance (ß) away from X.

The above conditions for moving the prototypes guarantee a better approximation of the decision boundary between the prototypes.

The software package used to conduct the ANN analysis is the Neuralyst function available on Microsoft Excel.

Linear Multiple Discriminant Analysis

Discriminant analysis is the conventional statistical technique commonly used to investigate problems of classification of a dependent variable based on a set constituted by an independent variable. For example, a lending bank might be interested in those qualities, which distinguish a good credit risk from a bad one. The software package used to conduct the discriminant analysis is SPSS (Statistical

Package for Social Sciences). The concept used is that linear combinations (called functions) of two or more predictor variable/s serve as a basis for classification of data into two or more groups. By considering the variables simultaneously, discriminant analysis will incorporate important information about their relationships. For functions to be optimal if has to be assumed that sample comes from a multivariate normal population and population covariance is same as that of sample covariance.
The linear discriminant equation:

$$D = B (1) X (1) + B (2) X (2) +\ldots+B (N) X (N) + C$$

Where X is the values of independent variables and the B's are co-efficient estimated from the data. The B's are chosen so that the discriminant function differs as much as possible between the groups or for the discriminant scores the ratio - Between-groups sum of squares/within-groups sum of squares is maximum.

Ideally, if there are N independent variables in discriminant analysis, it gives N-1 independent functions, which together determine groupings. Nevertheless, based on Wilk's Lambda statistic or U-statistic those functions are eliminated for which within group variability is not significantly different from across the group variability.

Using the discriminating function scores, the data are classified into one group or other. SPSS gives the classification output in form of confusion matrix and also for individual cases. In case-wise output, it gives the group into which a case can be classified based on discriminant functions scores and the group to which it actually belongs. It also gives summary in terms of percentage of cases correctly classified by analysis and percentage of cases incorrectly classified. This is used as a measure for comparison against the similar results obtained from the Artificial Neural Networks. Once derived, discriminant functions can be used for the prediction of new cases, which are not used in building the model. The percentage of cases correctly classified in this situation gives the actual effectiveness of the model. As stated earlier, SPSS is used for discriminant analysis. Statistical techniques like discriminant analysis and logistic regression are also used by Ganesalingam and Kumar (2001) in detecting financial distress and Altman (1968) in prediction of corporate bankruptcy. Frydman, Altman and Kao (1985) used various recursive partitioning techniques for financial classification.

For the ANN techniques, data set is split into two parts - major part (66 data vectors) are used for analysis and building the model and remaining part (10 data vectors) are used exclusively for prediction of rating. The original 76 data vectors are also used to compare classification of model's prediction with actual rating. The discriminant analysis model uses all 76 data vectors
A confusion matrix is prepared for two techniques to indicate the percentage of correct ratings as classified by model of the total actual ratings. A confusion matrix is nothing but a matrix which summarized by the percentage, classifications by model into separate categories) those classifications which are correct (same as actual classifications) and those classifications which are incorrect (different from actual classifications).

IV. DATA FINDINGS

Discriminant Analysis

Discriminant analysis using SPSS software resulted in a 4 significant functions model, which, classified the data based on independent variables into five rating classes. The model was able to classify 52.6 percent of the cases correctly.

Classification Results for Discriminant Analysis (a)

			Predicted Group Membership					Total
		RATING	1.00	2.00	3.00	4.00	5.00	
Original	Count	1.00	19	6	1	1	0	27
		2.00	7	12	2	1	0	22
		3.00	7	5	7	0	0	19
		4.00	0	4	0	2	0	6
		5.00	0	0	2	0	0	2
	%	1.00	70.4	22.2	3.7	3.7	.0	100.0
		2.00	31.8	54.5	9.1	4.5	.0	100.0
		3.00	36.8	26.3	36.8	.0	.0	100.0
		4.00	.0	66.7	.0	33.3	.0	100.0
		5.00	.0	.0	100.0	.0	.0	100.0

(a) 52.6% of original grouped cases correctly classified.

Artificial Neural Networks

Using a three-layered network model consisting of 14 input layers, 3 hidden layers and 1 output layer at an 85 percent confidence interval, the ANN model was able to classify 70 percent of the cases correctly. As stated earlier, the Neuralyst function in MS Excel was used to conduct ANN analysis. 66 out of the 76 original cases (87 percent) of the data was taken for the Training Set and the remaining 10 cases (13 percent) accounted for the Testing Set.

INTERPRETATION OF THE FINDINGS

Comparative analysis shows that the ANN model performed better.

Model	Percentage of Cases classified correctly
Artificial Neural Networks	70
Discriminant Analysis	52.6

The ANN model captured the hidden relationships between the financial parameters and associated expert rating more effectively than conventional discriminant analysis. This also proves to a significant extent that an expert analysis of a company's debt obligation is reflected by its current financial parameters. We can easily infer from the results of the analyses that an ANN is more effective in capturing hidden relationships, which are difficult to be captured by discriminant analysis.

However, it is to be realized that for issues of new companies and for new projects, which significantly modify existing operational, marketing, financial, personnel projections of the existing company are not amenable to this type of analysis. In those cases, subjective judgement of an expert alone can justify a rating, because financial parameters either do not exist or they are obviously irrelevant.

V. CONCLUSIONS

The study confirms the initial hypothesis that financial parameters reflect, to a significant extent, the subjective and objective factors used by an expert while rating a debt obligation. The hidden relationships are captured more effectively by Artificial Neural Network models compared to conventional discriminant analysis. It is to be emphasized that the findings in no way suggest substitution of experts by a software model, rather the ANN model rating can be used as a bench mark indication from which expert can start his analysis. Therefore, an ANN model can successfully complement the expert analysis. The advantages of such an approach are:

1. Reduction in time taken for rating an issue, because routine analysis can be delegated to software and machine.
2. Expert can fountain the rating based on his judgment of qualitative factors or he can overrule the results of software.
3. ANN model can be used as one more check or filter mechanism while awarding the rating.
4. There is a chance to automate the rating process if expert work closely with model builder and together it is possible to capture subjective information on quantitative scale. This will be possible only if sufficient numbers of proven common rules are framed that can capture the various aspects affecting credit-worthiness of company.

SCOPE FOR FURTHER RESEARCH

Further studies in this area can be carried out in following directions:

1. A comparative study of conventional analysis and the ANN model with much larger data and more variables (inclusion of industry and environment variables) to give more validity to findings.
2. Development of rule based expert systems to capture subjective judgments of expert which along with the financial parameters to be used in building a more effective ANN Model.
3. Application of ANN model to evaluate the credit worthiness of customers by banks and other lending institutions.

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APPENDIX 1

Original Data used for Analyse

Company Name	Long term	Fixed Deposit	Short Term	Rating
Addison & Co. Ltd.		FAA		2
Apcotex Lattices Ltd.	BBB+		P2+	4
Apollo Hospitals Ent. Ltd.	AA-	FAA+		2
Astra-IDL Ltd.		FAA+		2
Atul Ltd.	BB+			5
Bajaj Auto Ltd.	AAA	FAAA	P1+	1
Balmer Lawrie-Van Leer Ltd.	BB			5
BASF India Ltd.	AAA	FAAA	P1+	1
Bharat Gears Ltd.	BBB+			4
BPL Ltd.	A+	FA+	P1	3
Brakes India Ltd.			P1+	1
Centak Chemicals Ltd.	AA			2
Century Plyboards (India) Ltd.			P2+	3
Chambal Fertilizers & Chemicals Ltd.	A+	FAA-		3
Ciba Speciality Chemicals Ltd.			P1+	1
Citurgia Biochemicals Ltd.			P1	2
Colour Chem Ltd.			P1+	1
Cummins India Ltd.		FAAA	P1+	1
Dabur India Ltd.	AA	FAA+	P1+	2
Eicher India Ltd.		FA-		3
Ennore Foundries Ltd.	BBB-			4
Essel Packaging India Ltd.	AA			2
FAL Industries Ltd.		FA		3
Fenner(India) Ltd.	AA-	FAA	P1+	2
Fisher-Rosemount India Ltd.			P1+	1
GE (Lighting) India Ltd.			P1+	1
Gestetner India Ltd.			P1	2
Glenmark Pharmaceuticals Ltd.	AA		P1+	2
Goetze India Ltd.		FA+	P1	3
Goodlass Nerolac Paints Ltd.			P1+	1

Hero Honda Motors Ltd.	AAA	FAAA	P1+	1
Highway Cycles India Ltd.			P1+	1
Himatsingka Seide Ltd.			P1+	2
Hitech Gears Ltd.			P1	1
Hoechst Marion Roussel Ltd.	AAA		P1+	1
India Nippon Electricals Ltd.		FAAA		1
India Pistons Ltd.	AA-	FAA	P1+	2
Indian Explosives Ltd.			P1+	1
Indian Petrochemicals Corp. Ltd.	AA-	FAA	P1+	1
Ingersoll-Rand (India) Ltd.			P1+	2
Jagran Prakashan Ltd.	AA-			3
Jay Bharat Maruti Ltd.			P1	2
Kirloskar Brothers Ltd.		FA+	P1	3
LG Electronics India Ltd.	AA		P1+	1
Merind Ltd.	A	FA+		4
Munjal Showa Ltd.			P1+	1
Novartis India Ltd.			P1+	3
Parke-Davis (India) Ltd.			P1+	1
Perfect Circle Victor Ltd.	A+			4
Precot Mills Ltd.			P1+	2
Premier Auto Electric Ltd.		FB+		4
Premier Instruments and Controls Ltd.		FAA		3
Purolator India Ltd.	BBB+	FA		2
Rajapalayam Mills Ltd.	A+		P1	3
Ramaraju Surgical Cotton Mills Ltd.			P1	1
Redington India Ltd.			P1+	3
Sai Service Station Ltd.		FA		3
Sanghvi Movers Ltd.	A	FA+		3
Sona Koyo Steering Systems Ltd.	A			2
Sri Vishnu Shankar Mills Ltd.			P1	1
Sudarshan Chemicals industries Ltd.			P1+	2
Tata SSL Ltd.	AA-		P1+	2
Tata Yodogawa Ltd.		FAA	P1+	3
Twenty First Century Printers Ltd.	A+			3
UDV India Ltd.			P1+	1
Ultramarine Pigments Ltd.			P1+	1
Vam Organic Chemicals Ltd.		FA-		2

Vardhaman Polytex Ltd.	A+		3
Vardhaman Spinning & General Mills Ltd.	AA-	P1+	2
Vesuvius India Ltd.		P1+	1
Vinyl Chemicals (India) Ltd.		P1	1
Widia India Ltd.		P1+	1
Wipro GE Medical Systems Ltd.		P1+	1
Wockhardt Life Sciences Ltd.	A		3
Wockhardt Ltd.	AA+	P1+	2
Xerox Modicorp Ltd.	A+	P1	3

APPENDIX II

Rating Scales[1]

Long Term Rating Scales

High Investment Grades

AAA
(Triple A) Highest Safety

Debentures rated `**AAA'** are judged to offer highest safety of timely payment of interest and principal. Though the circumstances providing this degree of safety are likely to change, such changes as can be envisaged are most unlikely to affect adversely the fundamentally strong position of such issues.

AA
(Double A) High Safety

Debentures rated **'AA'** are judged to offer high safety of timely payment of interest and principal. They differ in safety from `**AAA'** issues only marginally.

Investment Grades

A
Adequate Safety

Debentures rated `**A'** are judged to offer adequate safety of timely payment of interest and principal; however, changes in circumstances can adversely affect such issues more than those in the higher rated categories.

BBB
(Triple B) Moderate Safety

Debentures rated `**BBB'** are judged to offer sufficient safety of timely payment of interest and principal for the present; however, changing circumstances are more likely to lead to a weakened capacity to pay interest and repay principal than for debentures in higher rated categories.

Speculative Grades

BB
(Double B) Inadequate Safety

Debentures rated `**BB'** are judged to carry inadequate safety of timely payment of interest and principal; while they are less susceptible to default than other speculative grade debentures in the immediate future, the uncertainties that the issuer faces could lead to inadequate capacity to make timely interest and principal payments.

[1] www.crisil.com

B High Risk	Debentures rated **`B'** are judged to have greater susceptibility to default; while currently interest and principal payments are met, adverse business or economic conditions would lead to lack of ability or willingness to pay interest or principal.
C Substantial Risk	Debentures rated **`C'** are judged to have factors present that make them vulnerable to default; timely payment of interest and principal is possible only if favourable circumstances continue.
D In Default	Debentures rated **`D'** are in default and in arrears of interest or principal payments or are expected to default on maturity. Such debentures are extremely speculative and returns from these debentures may be realized only on reorganisation or liquidation.
Note:	1) CRISIL may apply **"+"** (plus) or **"-"** (minus) signs for ratings from AA to D to reflect comparative standing within the category. 2) The contents within parenthesis are a guide to the pronunciation of the rating symbols. 3) Preference share rating symbols are identical to debenture rating symbols except that the letters "pf" are prefixed to the debenture rating symbols, e.g. pfAAA ("pf Triple A").

FAAA ("F Triple A") Highest Safety	This rating indicates that degree of safety regarding timely payment of interest and principal is very strong.
FAA ("F Double A") High Safety	This rating indicates that the degree of safety regarding timely payment of interest and principal is strong. However, the relative degree of safety is not as high as for fixed deposits with "FAAA" rating.
FA Adequate Safety	This rating indicates inadequate safety of timely payment of interest and principal. Such issues are less susceptible to default than fixed deposits rated below this category, but the uncertainties that the issuer faces could lead to inadequate capacity to make timely interest and principal payments.
FB Inadequate Safety	This rating indicates inadequate safety of timely payment of interest and principal. Such issues are less susceptible to default than fixed deposits rated below this category, but the uncertainties that the issuer faces could lead to inadequate capacity to make timely interest and principal payments.
FC High Risk	This rating indicates that the degree of safety regarding timely payment of interest and principal is doubtful. Such issues have factors at present that make them vulnerable to default; adverse business or economic conditions would lead to lack of ability or willingness to pay interest or principal.

FD Default	This rating indicates that the issue is either in default or is expected to be in default upon maturity.
Note:	1) CRISIL may apply **"+"** (plus) or **"-"** (minus) signs for ratings from FAA to FC to indicate the relative position within the rating category of the company raising fixed deposits. 2) The contents within parenthesis are a guide to the pronunciation of the rating symbols.

Crisil Rating For Short-Term Instruments (Commercial Paper)

P-1 This rating indicates that the degree of safety regarding timely payment on the instrument is very strong.

P-2 This rating indicates that the degree of safety regarding timely payment on the instrument is strong; however, the relative degree of safety is lower than that for instruments rated "P-1".

P-3 This rating indicates that the degree of safety regarding timely payment on the instrument is adequate; however, the instrument is more vulnerable to the adverse effects of changing circumstances than an instrument rated in the two higher categories.

P-4 This rating indicates that the degree of safety regarding timely payment on the instrument is minimal and it is likely to be adversely affected by short-term adversity or less favourable conditions.

P-5 This rating indicates that the instrument is expected to be in default on maturity or is in default.

Note: CRISIL may apply **"+"** (plus) sign for ratings from P-1 to P-3 to reflect a comparatively higher standing within the category.

APPENDIX III

Rating	Debenture	Long Term	Short Term
1	AAA	FAAA	P1+
2	AA + or -	FAA + or -	P1
3	A + or -	FA + or -	P2+
4	BBB + or -	FB + or -	P2
5	BB + or -	FC + or -	P3+
6	B + or -	FD	P3
7	C + or -	-	P4
8	D	-	P5

Note: No ratings were recorded below BB for debenture symbols, FB for long-term symbols and P2+ for short-term symbols.

Table used to derive rating categories for scaling of data