Bankruptcy Prediction of Financially Distressed Companies using Independent Component Analysis and Fuzzy Support Vector Machines

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Abstract—The aim of research is to model the dependency of enterprises on their financial ratios for predicting bankruptcy using artificial neural networks combined with fuzzy logic. A sample of companies which are financially distressed but not yet bankrupt is considered for conducting experiments. The data extracted from financial reports of financially distressed companies for past five years forms the basis for carrying out prediction. Independent Component Analysis has been applied on the input dataset comprising of financial ratios to choose the most significant ratios to be considered as input to the neuro-fuzzy network. A data set of size 1030 consisting of five variables was used for training and of size 350 was used for testing the network’s performance. In this way the model predicts the bankruptcy status of the enterprises with minimal training errors. A linguistic diagnosis of failure or financial problems of the enterprises is done using the fuzzy rule-base for support vector machines. The proposed model can be utilized by stakeholders of a financial distressed company for determining its future status. It can also be used by managers of the enterprises to take preventive measures to deal with financial crises.

Index Terms—Financial distress, Bankruptcy prediction, Financial ratios, Independent Component Analysis, Fuzzy Support Vector Machines.

I. INTRODUCTION

Bankruptcy prediction is widely studied for more than 4 decades for its significant impact on bank’s lending decisions and profitability. The reason lies in the mass of interested people in forecasts pertaining to financial strength of companies. It includes investors, auditors, creditors and employees which are in one way or other affected by corporate failure. A right prediction of bankruptcy is of great importance for financial institutions. Not only the stakeholders, but the financial institutions also are influenced by the financial condition of companies they have given loan. Bankruptcy is a legal proceeding by which a company/individual declares its inability to pay his bills, gives a chance to catch up on missed payments, gets a fresh financial start by temporarily or permanently preventing creditors from collecting debts, and sustain current operations. The result of bankruptcy prediction has multi-fold advantages. As pointed out by Atiya [6], if bankruptcy can be predicted accurately well in advance, it may guide bank authorities for taking decisions pertaining to loan approvals and may help in assessment of credit risk of bank loan portfolios. Most importantly, the prediction may be considered as an early warning facility for borrowing companies.

Financial ratios play an important role in assessing the financial status of a company. Ratios measure a number of features of a commercial company or company to analyze their financial statements. There are a large number of homogeneous financial ratios utilized for assessment of the financial state of a company. Each ratio gives information about factors such as the earning power, solvency, efficiency, and debt load of a business. This is the reason why financial ratios are considered to be the most important entity in identification and early warning of impending financial crises. These ratios are utilized by present and perspective stakeholders of the company differently; by shareholders to continue business with the company or not, by creditors to decide whether to provide resources in future or not, and by managers to monitor the financial performance of the company for forming strategies and initiatives to take corrective steps. Financial ratios are also used by security analysts for the purpose of pinpointing the strengths and weaknesses of companies.

Bankruptcy prediction is important not only to analysts and practitioners, but to commercial loan agencies, bonding companies, investors and even clients to avoid huge economic losses. It is also important to the company in predicting its own financial distress to provide new direction of the company. Not all the financially distressed companies experience bankruptcy. Although the two terms financial distress and bankruptcy seems to be same, but in essence there is a small difference between the two. When a company faces monetary problems in paying off its debts and payable bills, it is believed to be or going to be in a state of financial distress. If eventually, the company comes
up with enough money to make payments to suppliers and wages to its employees, it is on the safe side of danger line. But, if this is not made possible, it falls on the other side and is declared bankrupt. Sometimes, a financially distressed company declares itself bankrupt to protect from creditors interested in receiving instant payments.

The purpose of this work is to examine the efficacy of Independent Component Analysis (ICA) followed by SVM with fuzzy membership function termed as Fuzzy Support Vector Machine (FSVM) to bankruptcy analysis. FSVM is implemented for analyzing financial ratios obtained by ICA. There are a variety of ratios under various categories which are used by financial analysts and managers of the companies to take financial decisions. Choosing the right ratios for analysis is a key judgment in itself. From a keen review of ratios in literature, we have chosen 12 candidate ratios for bankruptcy prediction. We wish to find statistically independent ratios which are uncorrelated. This means that the value of any one of the ratios must not give any information on the values of the other ratios. ICA being a statistical and computational technique, allows separating statistically independent inputs, forms the choice of ICA in our model. Secondly, it is a well known fact that financial ratios are fuzzy in nature. There is a lot of similar work available in literature and discussed in the paper. All these methodologies yield satisfactory results, but at the same time they lack at a common point i.e. dealing with uncertainty in these ratios. The fuzziness in financial ratios is the driving factor behind choice of this approach.

The rest of the paper is organized as follows. Section II reviews prior work on bankruptcy and Neural Networks. Section III presents the proposed model for bankruptcy prediction using ICA and FSVM. Section IV discusses experimental ratio data under consideration and selections made. Section V demonstrates the test results and at the end, Section VI summarizes findings and conclusions.

II. REVIEW OF EXISTING WORK

The pioneer work in bankruptcy prediction was done by Smith & Winakor [45] in 1935. After that, a variety of models can be seen in literature in the area of bankruptcy prediction considering diverse factors with application of various techniques and methods. Early work shows significant difference in ratios of failing companies and successful companies [36]. Boritz & Kennedy [10] modeled a 14-factor neural network. The number of factors considered in other models ranges from one to 57 factors. Edfors [18] developed a model specifically for prediction of small business failure. Sinkey’s [44] model was aimed at prediction of bank failure. Some of the earliest bankruptcy studies that used Discriminant Analysis to identify failing companies include [3], [9], [34].

Shumway [43] developed a hazard model for forecasting bankruptcy combining both accounting and market data whereas Jones & Hensher [29] used a mixed logit model to predict company financial distress. Mensah [34] used both multivariate discriminant analysis and logit analysis to develop models in his study. Kim & Han [31] used Genetic Algorithm (GA) based data mining for discovering bankruptcy decision rules from experts’ qualitative decisions using cases of 772 Korean companies to define six qualitative factors. Etemadi et al. [19] used genetic programming to predict the bankruptcy for Iranian companies and compared the prediction results with Multiple Discriminant Analysis (MDA). The survey results showed 77% accuracy of MDA, while 94% of genetic programming in the same time. The study by Cho et al. [12] used Case Base Reasoning (CBR) whose results showed that this approach can increase accuracy of prediction models. Anandarajan et al. [4] examined the prediction of corporate bankruptcy by GA and MDA and the results showed better accuracy of GA as compared to MDA. Back et al. [7] used three alternative techniques-linear discriminant analysis, logit analysis and genetic algorithms-that can be used to empirically select predictors for neural networks in failure prediction. They found that the best prediction results were achieved when using genetic algorithms. Sancho et al. [39] presented a genetic programming approach to predict insolvency of non-life insurance companies and compared the results with other classification algorithms like Support Vector Machine and Rough Set approach. They found genetic programming methodology to be most suitable support decision method. Tam & Kiang [46], [47] considered the problem of bank failure prediction and compared between several methods: MDA, LR, K-nearest neighbor, ID3 classification algorithm, single-layer network, and multilayer network. Merkevicius et al. [35] used discriminant analysis together with self organizing maps to construct a hybrid SOM-Altman model for bankruptcy prediction in order to find optimal weights for ratios of Altman model [3].

Prediction of bankruptcy status of companies has always remained a major area of research interest for accounting and finance people. There exist extensive studies in this area using statistical approaches [3], [10] and artificial intelligence approaches [8], [15], [32], [37], [57]. Studies show that neural network models offer higher predictive accuracies than statistical methods and other AI methods such as inductive learning and genetic algorithm [33]. Chung and Tam [13] compared the performance of two inductive learning algorithms (ID3 and AQ) and NNs using two measures; the predictive accuracy and the representation capability. Results generated by the ID3 and AQ are more explainable yet they have less predictive accuracy than NNs. They found predictive accuracy of ID3 and AQ to be 79.5% while that of NN to be 85.3%. Tung et al. [50] showed that computational model build on mathematical formalization by hybridizing statistical and artificial intelligence approach can analyze complex phenomena like predicting bank failures. In his study [48] studied that the traditional approach considering various
quantitative as well as subjective factors, such as leverage, earnings, reputation, etc., through a scoring system. The problem with this approach is the subjective aspect of the prediction, which makes it difficult to make consistent estimates. This gives rise to a need to develop fair prediction model which can serve as an early warning system for defaulters.

Atiya [6] reviewed the problem of bankruptcy prediction using NNs. He aimed at improving the performance of NN through better training methods on inputs extracted from the equity markets. He gave a number of reasons to show that a nonlinear approach like neural network is superior to a linear approach like statistical approach. Altman [2] developed the most acceptable Z-score model of bankruptcy prediction. His five variable Z-score model using multiple discrimination analysis showed strong predictive power. Arora & Saini [5] gave a new direction to Altman’s ratios by putting forward a time series model for predicting bankruptcy via hybrid system of neural network and fuzzy logic. Combined with Altman’s Z-score, their ANFIS model was found to have ability to predict the financial strength of companies at any future time.

Originally, SVM was developed for pattern recognition problems and later it has been applied for isolated handwritten digit recognition [41], text categorization [28], speaker identification [40] and mechanical systems [26]. SVM have also been applied for bankruptcy prediction by Haardle, Moro, & Schaefer, [23] and compared with NN, MDA and learning vector quantization (LVQ) by Fan & Palani [20]. SVM was observed to obtain best results of around 70% accuracy followed by NN of around 68%, followed by LVQ of around 63%, followed by Multivariate Discriminant Analysis (MDA) of around 63%. SVM has yielded excellent generalization performance that is significantly better than that of competing methods. Studies that used SVM to predict financial failure show that SVM is better than NN and statistical methods in predicting the bankruptcy [38].

Shin et al. [42] used SVM to compare the results with neural networks, in the bankruptcy prediction process. The results also showed more accuracy and generalization of SVM compared with the NN’s. Classical SVM has been applied in various financial fields for credit ratings and ratings evaluation [11], financial time series forecasting [30] and bankruptcy analysis [21]. Combination with other intelligent techniques, such as Bayesian inference [22], genetic algorithms [1], fuzzy SVM approach [25], rough sets [52], ant colony optimization [58] and particle swarm optimization [56], SVM reported effective applications. Danenas et al. [17] presented an empirical evaluation of SVM-based classifiers applied for credit risk evaluation task. His results show that linear SVM classifiers, together with gradient descend based SVM classifiers and Core Vector Machines algorithms, can be a good choice for implementing SVM-based credit risk evaluation model. A fast SVM-based Core Vector Machines (CVM) offers promising results and is proved to be a lot faster than SVM implementations with ability to perform fast classification or regression tasks on huge datasets [49]. These researches showed that hybrid modeling based approach proved itself as reliable technique which allows obtaining better results than using SVM or other techniques separately.

III. PROPOSED MODEL

Research of several years has revealed that neural networks perform well in business classifications including bankruptcy prediction. As a matter of fact, all the inputs to neural networks cannot be always measured precisely. Consequently, an approach consisting of neural network with fuzzy inputs is needed to solve the problem in hand. Thus, a Fuzzy SVM has been trained on the training set chosen to be a random mix of financially distressed bankrupt and non-bankrupt companies to accurately predict their bankruptcy status in future.

A. Independent Component Analysis

Independent Component Analysis (ICA) is a signal processing technique whose goal is to express a set of random variables as a linear combination of statistically independent component variables [16]. The main applications of ICA vary from blind source separation and feature selection to blind convolution. In its simplest form, there are $m$ scalar random variables $v_1, v_2, \ldots, v_m$ which are linear combinations of $n$ unknown independent components $s_1, s_2, \ldots, s_n$ assumed to be statistically independent and zero mean. With the assumption of $n \leq m$, vector $v$ and vector $s$ have linear relationship represented by

$$v = \sum_{i=1}^{n} a_i s_i = As$$

(1)

Where, $A$ is an $m \times n$ matrix whose columns are denoted by $a_i$ for $i = 1, 2, \ldots, n$. The basic problem of ICA is to estimate components of $s_i$ from mixtures of $v_j$ or to estimate the value of $A$.

B. Fuzzy Support Vector Machines

Support Vector Machine models can solve a variety of classification problems, but Fuzzy Support Vector Machines (FSVM) classification have been found to be more effective over a period of time [24],[53],[27],[14]. In classical SVM, each sample is treated equally i.e. each input is observed to fully fall in one of the two classes. On the other hand, in many applications, outliers may not exactly belong to one of the predefined classes [55]. To
solve this problem, the basic functionality of SVM is extended to FSVM [33], where a fuzzy membership function is applied to each input data of SVM. In FSVM, each sample is given a fuzzy membership which denotes the attitude of the corresponding point toward one class. It also denotes the importance of the sample to the decision surface. Each input point makes it own different contribution to the learning of decision surface. The bigger the fuzzy membership, the more important is the corresponding point. The FSVM works as follows:

Suppose the training samples are $S = \{(X_i, y_i, s_i), i = 1, 2, ..., N\}$ where, each $X_i \in \mathbb{R}^N$ is a training sample and $y_i \in \{-1, +1\}$ represents its class label, $s_i (i=1,2,...N)$ is a fuzzy membership which satisfies $\sigma \leq s_i \leq 1$ with a sufficiently small constant $\epsilon > 0$. Let a set $Q = \{X_i | X_i, y_i, s_i \in S\}$ contains two classes; one class contains such sample point $X_i$ with $y_i = +1$, say class $C^+$, then,

$$C^+ = \{X_i \in S \text{ and } y_i = +1\}$$

(2)

The other class contains sample points $X_i$ with $y_i = -1$, say class $C^-$, and,

$$C^- = \{X_i \in S \text{ and } y_i = -1\}$$

(3)

It is obvious to note that

$$Q = C^+ \cup C^-$$

(4)

The quadratic problem for classification, then, can be described as follows:

$$\min \frac{1}{2} \|w\|^2 + c \sum_{i=1}^{m} s_i \xi_i$$

$$y_i (w^T \phi (X_i) + b) \geq 1 - \xi_i, \quad i = 1, ..., N$$

$$\xi_i \geq 0, \quad i = 1, ..., N$$

(5)

Where, $C$ is a constant. Since the fuzzy membership $s_i$ is the attitude of the corresponding point $X_i$ toward one class and the parameter $\xi_i$ is a measure of error in the SVM, the term $s_i \xi_i$ can be looked as a measure of error with different weights. It is noted that a smaller $s_i$ can reduce the effect of parameter $\xi_i$ in equation (5) so that the corresponding point $X_i$ can be treated as less important. Critical decision in solving given problem for FSVM is choosing appropriate fuzzy membership. As suggested, the fuzzy membership function for reducing the effect of outliers is a function of the distance between each data point and its corresponding class center, and the function is represented with parameters of the input space [33]. Given the sequence of training points (4), denote the mean of class $C^+$ and class $C^-$ as $X^+$ and $X^-$, respectively. The radius of class $C^+$ is

$$r_+ = \max \|X_i - X^+\| \quad \text{where } X_i \in C^+$$

(6)

and the radius of class $C^-$ is

$$r_- = \max \|X_i - X^-\| \quad \text{where } X_i \in C^-$$

(7)

The fuzzy membership $s_i$ is

$$s_i = \begin{cases} 
1 - \frac{\|X_i - X^+\|}{r_+ + \delta} & \text{if } X_i \in C^+ \\
1 - \frac{\|X_i - X^-\|}{r_- + \delta} & \text{if } X_i \in C^-
\end{cases}$$

(8)

Where, $\sigma > 0$ is a constant to avoid the case $s_i = 0$. The FSVM with the above membership function can achieve good performance since it is an average algorithm. A particular sample in the training set only contributes little to the final result and the effect of outliers can be eliminated by taking average on the samples [33].

IV. EXPERIMENTAL DATA

The experimental data has been obtained from the financial records of a good mix of financially distressed/non-distressed companies for years 2005-2010. The data used in this study comprise of the financial ratios of financially distressed companies which consist of both failed and non-failed companies. After a careful observation from literature, initially a set of 12 promising financial ratios are considered as shown in table I.

<table>
<thead>
<tr>
<th>TABLE I. INITIAL FINANCIAL RATIOS</th>
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</thead>
<tbody>
<tr>
<td>R1 : Quick Ratio</td>
</tr>
<tr>
<td>R2 : Current Ratio</td>
</tr>
<tr>
<td>R3 : EBIT/Total Assets</td>
</tr>
<tr>
<td>R4 : Total Assets Turnover Ratio</td>
</tr>
<tr>
<td>R5 : Retained Earnings/Total Sales</td>
</tr>
</tbody>
</table>

www_ijrcct.org
R6 : Return on Capital Employed  
R7 : Current Assets/Total Sales  
R8 : Inventory Turnover Ratio  
R9 : Debt equity Ratio  
R10 : Operating profit Margin

These ratios are then analyzed using Independent Component Analysis to minimize the dependency among them. As a result, 5 ratios are selected to be used as input in the next stage. Figure 1 shows the graphical representation of initial input dataset. ICA was applied to the input dataset of financial ratios of size 1030 to observe their behavior.

Fig. 1. Input Dataset for ICA

As seen from figure 1, it can be noted that some ratios follow the curl of other ratios. This implies that, these ratios contribute in determining the financial condition of a company in the same way other ratios do. Hence, the remaining ratios which are found to significantly vary independent of these ratios are selected for forming the training dataset.

Fig. 2 (a) Ratio Data Before ICA

It is apparent from figure 2 that the selected ratios are independent of each other. These ratios are EBIT/Total Assets, Total Assets Turnover Ratio, Retained Earning/Total Sales, Return on Capital Employed and Debt equity Ratio. Table II shows these ratios along with their respective variance in the values for companies in input dataset for FSVM.

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>R3 : EBIT/Total Assets</td>
<td>0.220805415</td>
</tr>
<tr>
<td>R4 : Total Assets Turnover Ratio</td>
<td>0.022498534</td>
</tr>
<tr>
<td>R5 : Retained Earnings/Total Sales</td>
<td>0.440306322</td>
</tr>
<tr>
<td>R6 : Return on Capital Employed</td>
<td>1.917666146</td>
</tr>
<tr>
<td>R9 : Debt equity Ratio</td>
<td>0.884790985</td>
</tr>
</tbody>
</table>

V. SIMULATION RESULTS

The model with 5 inputs for financial ratios and single output for bankruptcy result is developed in MATLAB. The input is fuzzy values of financial ratios and output is either 1 or 0 to signify whether the given financially distressed company is going to be bankrupt in future or not. A Gaussian membership function is selected to obtain smooth, continuously and infinitely differentiable hypersurface of fuzzy model and improve the reliability and robustness of the system.

Table III presents performance of FSVM on variations in the parameter values on a fix training data size of 1030. At any time the values of one of the parameters are changed to examine its effect on FSVM keeping other parameters constant. It can be observed that the model converges in more iteration with the increase in cost parameter with less number of support vectors giving more accurate prediction results. After cost 700, the prediction accuracy of the model is observed to be constant which means that there is no need of further increase in cost.
It is evident that with 1030 training sets in the data, the machine generates 342 support vectors with default cost (1) and default curvature (1/k=1/5=0.2) and converges in 202 iterations. Table IV demonstrates some sample data to validate that the prediction error is almost insignificant.

<table>
<thead>
<tr>
<th>Training Parameters</th>
<th>Training Result</th>
<th>Prediction Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kernel Function</td>
<td>Cost</td>
<td>Curvature of Curve</td>
</tr>
<tr>
<td>FSVM</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>ANFIS</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>SVM</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>500</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>700</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>900</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>1000</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>1200</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>1500</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>2000</td>
</tr>
<tr>
<td>Fuzzy SVM</td>
<td>2</td>
<td>1</td>
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<td>Fuzzy SVM</td>
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<td>Fuzzy SVM</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

When trained and tested on the same dataset, Adaptive Neuro-Fuzzy Inference System (ANFIS) is found to give following results. A comparative analysis can be done from the percentage accuracy in results for the two methodologies as shown in table V.

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Data Set Type</th>
<th>Accuracy (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSVM</td>
<td>Training</td>
<td>99.49</td>
</tr>
<tr>
<td>FSVM</td>
<td>Test</td>
<td>96.18</td>
</tr>
<tr>
<td>ANFIS</td>
<td>Training</td>
<td>93.12</td>
</tr>
<tr>
<td>ANFIS</td>
<td>Test</td>
<td>87.57</td>
</tr>
</tbody>
</table>

It is easy to observe from the table above that on the same size of training and test dataset, FSVM gives more promising results. The comparative analysis of clustering power of FSVM with ANFIS shows that former has superior clustering ability.

VI. CONCLUSION

The proposed model opens a new door for predicting the bankruptcy of companies which are showing signs of financial distress. There are chances that these companies may go bankrupt or may survive in future. This model fulfills the need of a robust model which can correctly predict the bankruptcy of a company belonging to any industry.

This paper contributes to the literature by examining all possible promising financial ratios for predicting bankruptcy of financially distressed companies. The model is potent due to its capability to deal with vagueness in the real scenario and its universality applicable in any industry. The application of fuzzy SVM generates near expected results. The non-linearity of financial ratios are reasonably handled in the model due to which it is found to be more efficient and less complicated as compared to other techniques. The generalization capability of fuzzy logic and SVM approach has been tested and found to give satisfactory results. ANFIS is one of the best methods known for classification, which in this model has also given around 88% accuracy, but FSVM has demonstrated its superiority by yielding more precise expected output of around 94%. Hence the model can be used by the stakeholders of financially distressed companies to determine their future bankruptcy status and to take timely decisions for these companies.

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