Effective prediction of Bankruptcy using Fuzzy Logic and Neural Networks

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***Abstract*— In financial sector, Bankruptcy has been a major issue from many years. Many researches are conducted for the prediction of Bankruptcy using many techniques. Only few studies are based on the Qualitative factors involved in bankruptcy detection. In this project, six most informative parameters (Financial flexibility, Industry risk, Management risk, Competitiveness, Operating risk and Credibility) having high entropy and information gain are considered. Although there are several techniques in use, there is a need for finding new approaches for improvement of the prediction accuracy. This paper proposes techniques involving Fuzzy Logic, Fuzzy Inference System using Fuzzy C-Means clustering and Deep Neural networks for prediction of the bankruptcy with remarkable accuracy. Also, a performance and efficiency comparison are made between the techniques used for effective prediction of bankruptcy.**

***Index Terms*— Fuzzy logic, Inference mechanisms, Neural networks, Qualitative factors.**

I. Introduction

Prediction of Bankruptcy is one of the primary issues to be solved in the finance sector. Advanced Systems to predict bankruptcy are needed to know the potential risk of the companies. Only Quantitative factors are considered in most of studies on bankruptcy prediction. Few other studies involve qualitative factors and new approaches. It is difficult to measure the quality of the factor from several hundreds of factors. There are many qualitative factors such as innovativeness, management quality, research, location of the company and growth of company. These factors are difficult to assess as most of them are not available in public. Many models are present for assessing quality of information and knowing what factors to be considered in this area. As the factors considered are purely subjective, it is hard to understand what kind of qualitative information is useful. There is a limited study being done to check if these qualitative measures are key success factors. An important thing to be consider is to know whether the qualitative information is properly measured and check if it can be used to measure the company success or not. Also, one more important thing is to choose the type of qualitative information used for the bankruptcy prediction. In this paper we used several methods involving concepts like fuzzy logic, fuzzy Inference system and deep neural networks for the prediction of the bankruptcy. We define the fuzzy sets for partitioning the universe into different fuzzy sets. Fuzzy systems have more advantage compared to the traditional approaches which only consider the values directly instead of converting to fuzzy sets. These fuzzy sets are further processed to predict the company/firm's chances of going to be a bankrupt or not bankrupt which in turn are fuzzy sets.

In second method, we have made use of Mamdani fuzzy inference system with a clustering algorithm. There are clustering algorithms like subtractive clustering, Fuzzy C-means clustering, Grid partitioning. We have used Fuzzy C-Means clustering algorithm along with Mamdani Fuzzy Inference System for prediction of bankruptcy.

For further analysis of systems predicting bankruptcy based on qualitative parameters, we have used deep neural network with various activation functions and many hidden layers.

All these techniques used in prediction of bankruptcy have shown good results with great accuracy proving that fuzzy logic and deep neural networks can be used in developing a strong system/model for effective prediction of bankruptcy status in real time scenario.

II. Problem Statement

As mentioned in abstract and introduction, prediction of bankruptcy and building a system to find bankruptcy status with higher accuracy is important as it is related to financial sector and reputation of an organization. Finding bankruptcy status is not an easy job as many parameters are involved. So, we must research different techniques for finding a novel system. If possible combine different methodologies to get an advanced prediction system. For prediction of bankruptcy the selection of parameters is very important. We have considered the qualitative parameters with high entropy and information gain. In this paper, we have made efforts to develop a good bank bankruptcy prediction system using three different approaches namely fuzzy logic, Fuzzy Inference system with Fuzzy C-means clustering and Deep neural networks. In next section, we will discuss in detail about the methods used and the results it produced and make a comparison between these techniques.

III. Literature Survey

There are many studies on bankruptcy prediction where most of these researches have considered quantitative information like the number of employees of an organization, turnover of an organization, number years of establishment, etc. Few of the techniques which were used in prediction of bankruptcy status are inductive learning and using an expert base which is constructed from the knowledge of the experts in this field.

Data mining techniques are being used in extracting the qualitative information from the huge database. Researches are being conducted to find the most important parameters to be considered while doing prediction and they are successfully able to get the most informative parameters. Entropy and Information Gain are considered for extracting most important parameters.

$$H(S) = \sum_{i}^{N} - P_i * log_2 P_i$$

$$G(S, A) = H(S) - \sum \frac{|S_v|}{|S|} H(S_v)$$

Where H(S) represents the entropy of the given data sample of length N and G (S, A) represents the information gain of the attribute A on the given sample data S.

The six most informative parameters in bankruptcy status prediction are as follows:

- Management Risk
- Financial Flexibility
- Credibility
- Competitiveness
- Industry Risk
- Operation Risk.

Qualitative parameters:

The following are the details of six qualitative factors that are considered in implementation of this project.

Industry risk refers to risk to a stock due to problems that stem not from within the company, but due to far wide-ranging problems that involves the industry indirectly or directly. For example, due to the online market development many instore selling stores have faced a lot of decrease in sales. The online market development is a technology advancement that might be unforeseen by the instore selling stores or companies. We have characterized these things into industry risk.

Management risk might occur due to the poor decisions made by the manager on behalf of the shareholders and the company which might reduce the share value of the company. In many cases such poor decisions have decreased the wealth of the shareholders.

Financial flexibility defines a organizations ability to react to unforeseen expenses and investment opportunities. Financial flexibility is generally calculated by examining the company's use of the ratio of the company's loan capital (debt) to the value of its common stock (equity) as well as money holdings. Companies with excellent financial flexibility are both able to take advantage of unexpected investment opportunities as well as survive tough economic times. Industries that are unable to respond efficiently to unforeseen problems or difficulties may lack the funds or wealth to survive long-term bear markets.

Credibility is nothing but trustworthiness. Credibility of a person or a organization can be known by the credit history, the reliability of the information and the relationship maintained with the financial institutes.

Competitiveness is the ability to provide services more efficiently than the related contender by sustaining the hardships similarly in known as well as uncharted situations. Competitiveness, in traded sector, is a direct measure of the firm's performance in the international marketplace. In the non-traded areas, competitiveness is the capacity to overpower the world's top organizations in value, quality and number of products and services. Giving a tough competition surely indicates the long run of the organization.

Operational risks can be due to the humanly errors or computational errors with in the industry that might be difficult to interpret.

The following table shows the risk factor and corresponding risk components.

Risk factor	Risk Components
Industry Risk(IR)	- Government Policies - Size and Growth of Market demand - Product life cycle - Stability of the market - Macroeconomics factors
Management Risk(MR)	- Ability of management - HR management - Short and Long-term business planning - Competitiveness
Financial Flexibility(FF)	- Direct Financing - Indirect Financing - Other third-party financing
Credibility(CR)	- Credit History - Reliability of Information - Relationship with financial institutions
Competitiveness(CO)	- Market position - Level of core capabilities - Differentiated strategies
Operational Risk(OR)	- Stability of transaction - Efficiency of production - Demand for product - Sales Diversification - Effectiveness of sale network

IV. Methods

I) Fuzzy Logic using Mamdani Fuzzy Inference System

The procedure of mapping a given input to output by employing fuzzy logic is defined as fuzzy inference. The procedure requires the use of fuzzy logic operators, membership functions and if-then rules. Fuzzy inference systems can be used in various fields such as data classification, data analysis and expert systems.

Membership functions stored in the fuzzy knowledge base system are used to convert the crisp input to a linguistic variable by the fuzzifier. Inference engine , converts the fuzzy input into the fuzzy output by using If-Then type fuzzy rules. Defuzzifier by using the membership functions analogous to the one used by the fuzzifier, converts the fuzzy output of the inference engine to crisp value.

The Mamdani and Sugeno fuzzy inference methods are most important types of fuzzy inference method. Most commonly seen inference method is the Mamdani fuzzy inference method. Mamdani and Assilian introduced this method. In this project the second step is application of Mamdani fuzzy inference system with c-means clustering algorithm.

The steps followed in Mamdani fuzzy inference system are:

- Fuzzifying by giving membership functions as input. We have six inputs as mentioned namely Industry risk, Management risk, Financial flexibility, Credibility, Competitiveness and Operating risk that are divided into three fuzzy variables Average, Positive and Negative. The output fuzzy variables defined are NB which refers to non-bankruptcy and B which refers bankruptcy.

Gaussian membership function is the membership function used in the Mamdani fuzzy inference system. Gaussian membership function is a 2-parameter function which are the mean and the variance. The below equation defines the gaussian membership function.

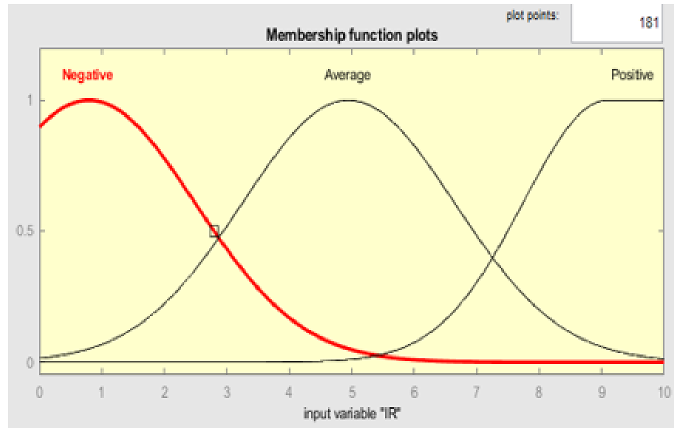
$$\mathrm{gaussian}(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}.$$

Where, c is the mean and
σ is the variance

The following are the fuzzy sets defined for Industrial risk.

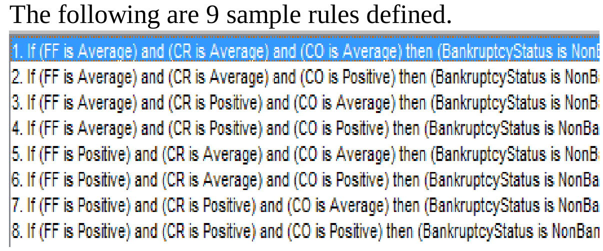
Industry Risk Fuzzy Set	Range	Membership Function
Positive	[0,10]	Gaussmf[1.36, 9.097]
Average	[0,10]	Gaussmf[1.7, 4.947]
Negative	[0,10]	Gaussmf[1.7, 0.7937]

The table represents the Industry risk fuzzy set for the 3 fuzzy variables namely Positive, Average and Negative. The ranges for all the three fuzzy variables are in between 0 and 10. The mean and variance for each fuzzy variable are represented in the table.



The above figure is the graphical representation of the membership functions. Similarly, we have defined fuzzy sets for other parameters.

- While defining fuzzy rule base, we used 3 input fuzzy variables and 2 output fuzzy variables fuzzy rule base is defined. There are total 67 rules defined in fuzzy rule base. The following is the sample rule used in this model using and operator between three input variables. The following are 9 sample rules defined.



Consider, If Financial flexibility is average and Credibility is Average, and Competitiveness is Average, then the chances of being bankrupt are high.

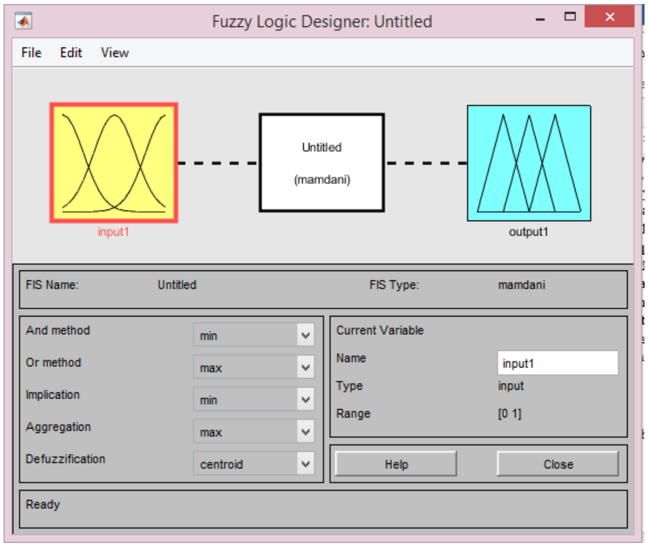
- To establish a rule strength according to the fuzzy rules by combining the fuzzified inputs.
- Calculating results of the rules by combining the output membership function the rule strength.
- Getting an output distribution by combining the results.
- The last step is output distribution de-fuzzification.

We have used Centroid method for defuzzification. The following is the formula to calculate the centroid.

$$z^* = \frac{\int \mu_{\underset{\sim}{B}}(z) \cdot z \, dz}{\int \mu_{\underset{\sim}{B}}(z) \, dz}$$

As the output membership functions are non-linear gaussian distribution, it is better to use compared to other membership functions like mean of max or weighted average method.

The following is the output of the fuzzy system developed.



II) Fuzzy Inference System using Fuzzy C-Means clustering.

As discussed in the above method where we have used Mamdani Fuzzy inference system with Fuzzy rule base, here we have used a Fuzzy inference system with Fuzzy C-means clustering.

We create a new fuzzy inference system with existing Mamdani fuzzy Inference system and Fuzzy C-Means Clustering. Let us see about the FCM clustering.

There are many clustering techniques like subtractive clustering, grid partitioning and Fuzzy C-means clustering. Fuzzy C-Means Clustering is one of the popular clustering technique and the accuracy of this technique is quite high. This clustering technique is also called as soft clustering. As fuzzy indicates that an item can belong to more than one set (here cluster). In FCM clustering, we have an objective function which must be minimized. The following is the objective function of FCM.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \quad , \quad 1 \le m < \infty$$

C is the number of clusters, N is the number of point in the set.

The following steps are involved in performing Fuzzy C-Means clustering.

1. Initially select the random cluster center. Let it be c.
2. Fuzzy membership is calculated using the below formula.

$$\mu_{ij} = 1 / \sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/m-1)}$$

Where d represents the Euclidian distance, m is fuzzy index.

3. Compute the fuzzy clusters as follows.

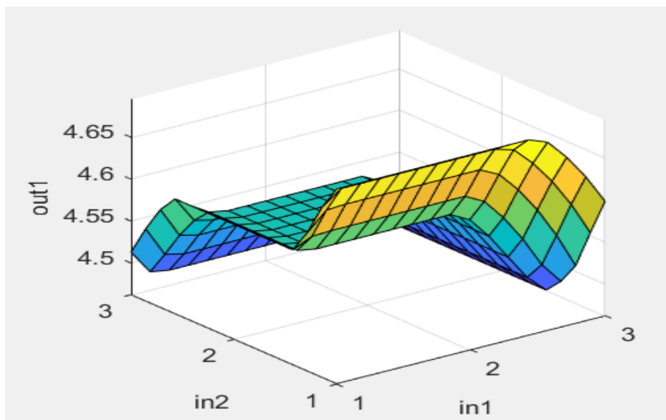
$$v_j = \left(\sum_{i=1}^{n} (\mu_{ij})^m x_i\right) / \left(\sum_{i=1}^{n} (\mu_{ij})^m\right), \forall j = 1, 2, \ldots..c$$

4. The above steps are repeated till the clusters converge.

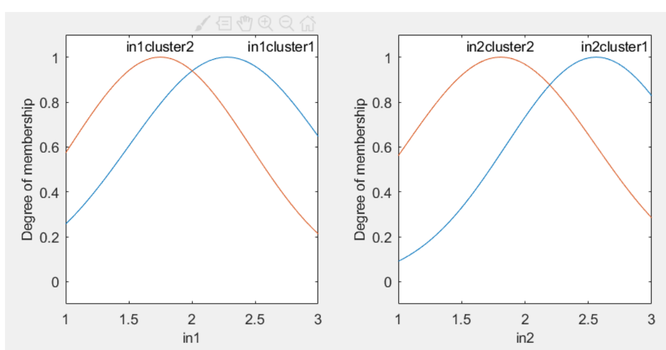
We created a new fuzzy inference system using a Mamdani fuzzy inference system and Fuzzy C-Means Clustering which is discussed above. We provide Industrial risk, Financial flexibility, Management Risk, Competitiveness, Credibility risk and operation risks information as input to the system.

We train the above system with the training data which account to 80% of total data.

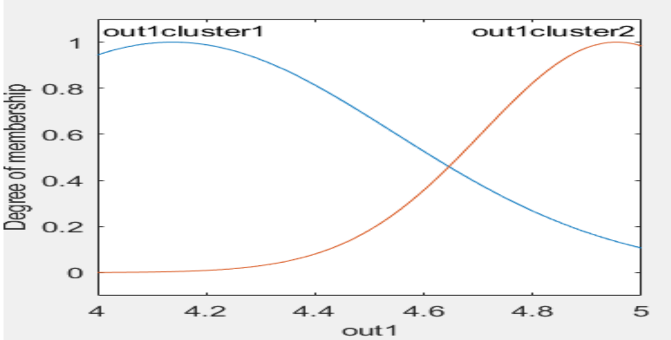
We have run the model for more than 20 iterations till the final clusters converge. The following fuzzy inference system is generated



For the six variables which are Financial flexibility, Management Risk, Competitiveness, Credibility risk and operation risks, we generate the membership for the belongingness to the output clusters which are Bankruptcy and Non-Bankruptcy based on the new system which has used FCM clustering. The following are the membership functions generated for the Management Risk(In2) and Industrial Risk(In1).



Similarly, we got membership functions for the other input variables. The following membership functions are for the output variables Bankruptcy(Cluster1) and Non-Bankruptcy(Cluster2).

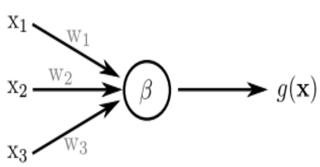


We got better results using this hybrid technique. The testing accuracy of this model is approximately 96% for the given dataset.

We have tried another approach using deep neural network which is explained in the next section.

III) Neural Networks:

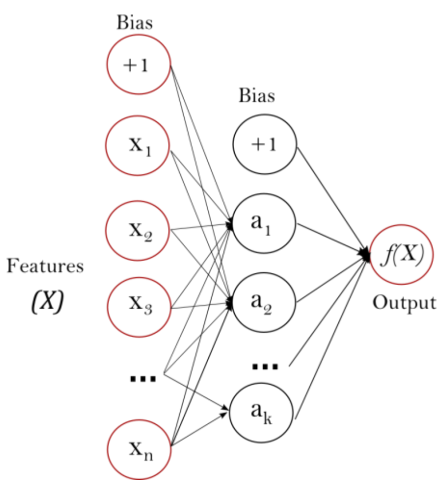
We have also used neural networks for the prediction of bankruptcy status using deep neural networks. A neural network with more than one hidden layer is known as deep neural network. For a neural network there are six inputs namely Management risk, Operational risk, Credibility, Competitiveness, Industrial risk and financial flexibility and two outputs namely Bankruptcy and non-Bankruptcy. Bankruptcy tell the chances of bankruptcy and Non-Bankruptcy tells the chances of not being bankrupt. There are many layers in between with different activation function. The following is an example of single layer perceptron.



The output g(x) of the single perceptron for given W's and B's is

$$g(\mathbf{x}) = \sigma(w_1 x_1 + w_2 x_2 + w_3 x_3 - \beta)$$

The following is an example of multilayer perceptron.



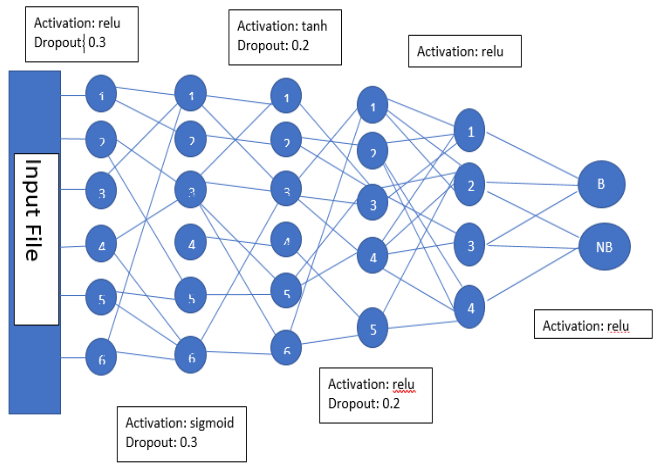
The output for multilayer perceptron is shown as below.

$$\boldsymbol{g}^{\ell}(\mathbf{x}) = \sigma(\mathbf{W}^{\ell}\boldsymbol{g}^{\ell-1}(\mathbf{x}) - \boldsymbol{\beta}_{\ell}).$$

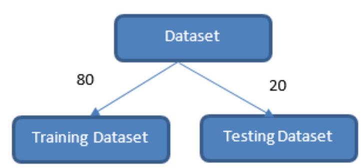
In our problem, we have 6 inputs features i.e., n=6 and outputs are g(x) and f(x). g(x) tell the bankruptcy status and f(x) tells the non-bankruptcy status.

Steps involved in performing this.

1. Import the data from Text file.
2. Preprocess the data to get the input features and corresponding output. We get [X Y], where X is input feature vector and Y is expected output label.
3. Build the model. Here we have used different activation functions for different layers with dropout. We used Relu, Sigmoid and tanh activation functions. We have fixed to these activation functions after checking many other activation functions. The below is the outline of the network we have used.



4. Split entire data into two parts: Training (80%) and Testing Dataset (20%). Usually, training data is of greater percentage than testing data.



5. Train the network with training data. Calculate the training accuracy and continue to run many epochs to obtain high accuracy.
6. Save the model.
7. Predict the outputs for testing data and get the accuracy.

We have run our neural network for 25, 50, 100, 125 epochs and 100 epoch had the highest accuracy of all.

Our neural network has produced the following result.

	true NB	true B	class precision
pred. NB	139	4	97.20%
pred. B	4	103	96.26%
class recall	97.20%	96.26%	

Accuracy of prediction of NB = True prediction NB / Actual NB
⇨ Accuracy prediction of NB = 139/139+4 ~ 97.20%
Accuracy of prediction of B = True prediction B / Actual B
⇨ Accuracy prediction of NB = 103/103+4 ~ 96.26 %
So, the average accuracy of prediction is approximately 96.8%

- We can get a confusion matrix which has information of True Positives, True Negatives, False Positives and False Negatives.
- Probability of Detection measure the correctness of the prediction.
- Probability of False Alarm mesures the falseness/ incorrectness of the prediction.
- We calculate the Probabilty of Detection(PD) as **PD = TP/ (TP + FN)**.
- We calculate the Probability of False Alarm(PF) as **PF = FP / (FP + TN)**

So, the overall average accuracy of the prediction is 96.8. This shows a better result than the fuzzy Inference system using FCM-clustering.

V. Conclusion

We have done the prediction of bankruptcy status when all the six qualitative factors are provided using Fuzzy logic, Fuzzy inference systems with Fuzzy C-Means Clustering and found that all the three models are given good results. Neural network leads in terms of accuracy and then followed by Fuzzy inference systems with FCM clustering. Deep neural networks with suitable number of hyperparameters and activation functions provides much better results with greater accuracy.

The following table shows the accuracy of the models in predicting the status of bankruptcy.

Method	**Accuracy**
FIS using Fuzzy C-Means classifier	96
Neural networks	96.8

VI. Future Work

- Improve the prediction of models using huge amount of data to build much accurate model
- Further analysis on the qualitative parameters. More the number of qualitative parameters gathered, better the model can be build.
- Using this system, we can alert banks/financial organizations about the chances of bankruptcy
- Check the accuracy using other techniques like linear regression, Random forests, etc.
- Testing the models on very large dataset to check the accuracy.

VII. References

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