BANK BANKRUPTCY PREDICTION USING MACHINE LEARNING ALGORITHMS

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Abstract

At the heart of every financial system, banks play the vital role of financial intermediaries. For an economy to have sustainable growth, it must have a stable banking system. In the last decade, the financial and banking industry has witnessed a plethora of changes and developments. These have led to new challenges and greater exposure to risk. In the aftermath of the 2008 financial crisis. This scenario has brought to the fore an increased requirement to predict bankruptcy. The purpose of this study is to actualise the prediction of Spanish bank bankruptcy and compare the accuracy of four algorithms which are Logistic Regression, Decision Tree, Extreme Gradient Boosting and Feed-Forward Back Propagation Neural Network. This study also reviews the various methods of bankruptcy prediction. The findings in the study show that Decision Tree had an accuracy of 81.25% by using the Gini criterion. Logistic Regression method had an accuracy of 86.36%. Extreme gradient boosting method had an accuracy of 90.625 %. Feed-Forward Back Propagation Neural Network method had an accuracy of 95.5%.

Key Words: Logistic Regression, Extreme Gradient Boosting, Decision tree, Feed-Forward Back Propagation Neural Network, Bankruptcy

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1 Introduction

In the world that we live in today, the financial system plays a very important role for each of the activities that are carried out. To facilitate these activities banks play a very important role. In the aftermath of the financial crisis of 2008, regulators around the world have become extremely cautious about the financial stability of their economy.

Predicting bankruptcy is a difficult exercise and many challenges have to be faced. The first important challenge is to choose the method or technique based on the nature of the data used in the study.In every financial system banks play a vital role in stimulating the growth of the economy. It pools the small savings of numerous households and provides loans to borrowers. This role of financial intermediation performed by the banks helps the surplus savings be utilised for investment purpose.In the recent times with the development and increasing complexity in financial instruments the risks and challenges faced by the banks have steadily increased. The government in a country must ensure that the interests of the depositors are protected and that financial stability ensues in a country.

Bank bankruptcies have a greater impact on the economy than bankruptcies of any other type. This is because a number of stakeholders depend on banks. A bank bankruptcy negatively impacts bank's shareholders, depositors, borrowers and other institutions that lend funds to banks.

Bankruptcy protection is an area of interest to many stakeholders right from 1960s. The financial performance of a bank or a firm is determined by various factors. These factors include:

1. The solvency of the firm at its inception,
2. its ability to generate cash from its operations,
3. the extent of its access to capital markets,
4. Its capability to deal sudden depletion of cash reserves.

To ascertain the financial stability of banks the regulators conduct an on-site study to determine the bank's CAMELS rating. This rating evaluates banks on the basis of six characteristics. They are capital adequacy, asset quality, management expertise, earnings strength, liquidity and sensitivity to market risk.

1.1 The Problem

A number of banks have gone bankrupt in the past few years. The occurrence of a bank bankruptcy affects a number of stakeholders. To avoid the incidence of a bankruptcy we have to predict bankruptcy accurately and take steps in order to prevent the same.

1.2 Objectives of Study

- To do an extensive literature Review on application of machine learning tools for Bankruptcy Prediction.
- To implement and test the efficiency and performance of one or more Machine Learning Techniques for Bankruptcy prediction.
- To identify factors which significantly impact the occurrence of Bankruptcy?

1.3 Scope of Study

- The literature review is based on the articles research papers accessible through EBSCO, and Science Direct.
- The study is based on secondary sources of data alone.
- The study is based on financial data of 66 Spanish banks from 1977-1985.
- Only nine financial ratios of the banks have been considered for the study.

Section 1 deals with Introduction to the study and defines the scope of the study.**Section 2** presents the literature review on topics of Bank bankruptcy prediction, application of neural networks and their comparative efficiency with respect to the machine learning tools.**Section3** deals with the overview of methodology used in the study. **Section4** elaborates the findings of the study and presents the data analysis and interpretation done.**Section5** provides the highlights of each Section and provides the summary and conclusion of the entire study. It also provides suggestions and recommendations for future work.

2 Literature Review

BirolYildiz and SonerAkkoc (2010) in their paper" ***Bankruptcy Prediction Using Neuro Fuzzy: An application in Turkish Banks*"** proposes the application of a combined model to predict Bankruptcy. They have used a combined model of Artificial Neural Network and Fuzzy Logic. The data used in the sample of this study is of 55 Turkish Banks.

The dataset contains 36 financial ratios which are categorised under six titles which are liquidity, asset quality, profitability, capital ratios, income expenditure structure and activity ratios. They performed the test bankrupt and non-bankrupt banks. At 5% level of significance they found differences between 24 financial ratios to be significant.The authors further used a factor analysis on the second dataset of 24 financial ratios. As an extraction method, is the principal component analysis was applied to the dataset.

The authors compared the prediction efficiency of the models which are multi-discriminant analysis, artificial neural network model, neuro-fuzzy model. From this study the authors concluded that the prediction accuracy of NF, ANN and MDA models are found at 90.91%, 86.36% and 81.82% respectively. Although all the models have given accuracies which do not differ much, the neuro-fuzzy model stands out from the rest of its capability to identify the variables used in the decision process.

Dr Roli Pradhan (2013) in her paper "***Application of BPNN for Bankruptcy Prediction*"** has estimated the internal parameters of Z score for HDFC Bank from 2000 to 2008. These values have been used to train Back Propagation Neural Networks. She further uses the Banks financial data pertaining to the years 2009 and 2010 for validation. The author has further worked to predict the data for the time period 2011 to 2015. In this paper she uses the Neural Network (1 – 5 – 4) which means the number of input rows are one, the hidden layers are five and the outcomes are four internal parameters. The financial data of the bank has been obtained from published balance sheets, profit and loss statements, CMIE database and RBI database.

KalyanNagarajand Amulyashree Sridhar (2015) in their paper "***A Predictive System for detection of Bankruptcy using Machine learning techniques*"** have used a Qualitative

Bankruptcy Dataset from UCI Machine Learning Repository. The authors have considered various soft computing techniques like Logistic Regression, Naïve Bayes classifier, Random Forest, Neural networks, Support vector machine to predict Bankruptcy. The results of the authors show that Support vector machine algorithm has the highest accuracy of prediction.

Yinhua Li, Yong Shi, Anqiang Huang, Haizhen Yang (2014) in their paper "***A New Method for Early Warning System of Commercial Banks: Hybrid of Trait Recognition and SVM***" have looked at the usefulness and the deficiencies of Trait Recognition Method. The authors propose combining the information encoding technique which is present in the Trait Recognition Method with SVM. The authors have described three advantages of new proposed method.

1. Firstly, the algorithm doesn't omit any vital information.
2. Secondly, it will give a clear result whether a bank is solvent or not.
3. And thirdly, it will consider correlation among two or three attributes through encoding process.

In this study the data of the banks has been collected from Federal Deposit Insurance Corporation (FDIC). They considered the data of 158 failed banks and correspondingly 158 non failed banks. Another 98 banks were used as sample data. The conclusion of the study was that the hybrid of TR and SVM outperforms TR.

Nidhi Arora and Jatinderkumar R. Saini(2014) in their paper "***Bankruptcy Prediction of Financially Distressed Companies using Independent Component Analysis and Fuzzy Support Vector Machines***" discuss about the efficiency of Independent Component Analysis followed by Fuzzy Support Vector Machines to predict Bankruptcy. The authors have selected 12 ratios which have to be statistically independent and correlated. The Popular SVM model has been used widely for resolving classification problems. In the usual SVM cases each sample is treated the same. The inputs for the SVM model fall in one of the two classes. But in some cases we have few outliers which we may need to consider. To solve this problem the authors in their paper consider a Fuzzy membership function as an input data for the SVM. The authors compared FVSM and ANFIS and concluded that the former has superior clustering ability.

GokhanTorna (2010) in his paper **"*Understanding Commercial Bank Failures in the Modern Banking Era*"** studies the reasons for healthy banks to become distressed and for distressed banks to fail. They look at the impact of Investment Banking, Venture capital and Brokerage services on the health of a bank. The hypothesis that the author has considered are:

1. "*Banks that practice modern banking activities and techniques are more likely to become financially troubled and/or insolvent.*
2. *The phenomena that result in a healthy bank becoming troubled are different from the phenomena that result in a troubled bank failing (or recovering).*
3. *Banks that practice traditional banking activities and techniques are no more or less likely to fail during the banking crises of the late-2000s than during the banking crises of late 1980s and early 1990s*". (Torna, 2010)

The data considered in the study is a sample which spans across all commercial banks in US from October 2007 to October 2009 obtained from FDIC. The results from this study show that factors causing a healthy bank to become distressed are different from those causing a distressed bank to fail.

A.Martin, V.Gayathri, G.Saranya, P.Gayathri, Dr.PrasannaVenkatesan(2011) in their paper "***A Hybrid Model for Bankruptcy Prediction Using Genetic Algorithm, Fuzzy C-Means And Mars***" discuss the efficiency of Fuzzy Neural Networks over Neural Networks. The authors say that FNN helps to overcome the black box approach but the learning capacity of the model reduces. In contrast to this the authors suggest Genetic Fuzzy Neural Networks (GFNN) overcome the black box approach and improve the learning capability.

IGNACIO OLMEDA and **EUGENIO FERNA´NDEZ(1997)** in their paper "***Hybrid classifiers for financial multi-criteria decision-making: the Case of bankruptcy prediction***"have looked at the banks in Spain. The Spanish banking system was impacted with a major crisis from 1977 to 1985. The monetary loss which resulted from this crisis has been estimated to be $ 12 billion. The authors have worked on the dataset of the Spanish banks. They have considered nine financial and economic ratios of 66 banks. The data for the failed banks has been taken from the financial statements issued before bankruptcy was declared. The financial data for the non-failed banks has been obtained from the 1982 statements.

This database was randomly split into two sets, Set 1 comprised of 34 banks (15 failed and 19 non-failed) and set 2 of 32 banks (14 failed and 18 non-failed). Set 1 was used for training and Set 2 was used for testing. After this process was reversed where in Set 2 was used for training and Set 1 was used for testing. In conclusion the authors stated that artificial neural network models can be considered better than both recently developed machine learning and statistical techniques. Another major finding from this study is that when one combines two or more methods, the predictions are generally more accurate. This is in comparison to applying a method individually to a given data set.

Roli Pradhan (2014) in her paper "***Z Score Estimation for Indian Banking Sector***" says that the basic concern of prediction is to evaluate the terms of credit and ensure repayment safely. In this paper the author has computed the Z score values for three public sector banks which are Oriental Bank of commerce, Punjab National Bank and State Bank of India. The predicted Z score value is useful when banks demand loans from RBI other funding organisations. The book formulae was used for computation of ratios which are further used as input parameters for the Neural Network. The author has used a Back Propagation Neural Network for prediction of ratios for the years 2008, 2009 and 2010. The Z score value for the sample banks has been forecasted up to 2020.

GamzeÖzeland **Nihal Ata Tutkun (2013)** in their paper "***Probabilistic Prediction of Bank Failures with Financial Ratios: An Empirical Study on Turkish Banks***" have studied the financial ratios of seventy banks which are part of the Turkish Banking system from 2000 to 2008. They have used the financial ratios and examined few failure prediction techniques such as Survival, Ordinary and Conditional logistic regression models. They concluded from their analysis that the bank is more likely to go bankrupt if it is unprofitable, small, highly leveraged, and has liquidity problems and less financial flexibility.

ChetteSrinivas Yadav and **Pallapothu Vijay (2015)** in their paper "***Predicting Bankruptcy: An Empirical Study Using Multiple Discriminant Analysis Models"***have used two Multiple Discriminant Analysis models for predicting bankruptcy using the financial data of Indian manufacturing companies. The study is over a period of five years 2009 to 2013. From the time Edward I. Altman came out with his Z score model in 1968 a number of researchers have brought out various models to predict bankruptcy. The purpose of this study was to identify the best MDA models that can accurately predict bankruptcy.(Vijay, 2015)

QeetharaKdhim Al-Shayeaand **GhalebAwad El-Refae (2012)** in their *papers "**Evaluation of Banks Insolvency Using Artificial Neural Networks"***have used Generalized Regression Neural Network to determine the explanatory variables which were used to predict insolvency. The authors used scaled conjugate gradient algorithm as the basis of the feed forward neural network. This model gave an accuracy approximately 91% in classifying the insolvent Spanish banks.

3 METHODOLOGY AND DESIGN OF THE STUDY

3.1 Nature of the Study

The study is primarily a quantitative study which uses machine learning tools to predict bank bankruptcy. The bankruptcy of a bank can be predicted by observing their financial ratios.
Most of the research work done about bank bankruptcy prediction have used either the Spanish banks dataset or the Turkish banks dataset. Some researchers have also used the data of the US banks.

To generate a good model the size of the data set must be large enough. Especially when working with artificial neural networks we will need a larger dataset. Since in ANN the dataset is split into three parts training set, validation set and testing set

For the purpose of this study two softwares have been used. To obtain the prediction accuracy for decision trees, logistic regression and extreme gradient boosting the software by name Python has been used. Python is an open source software available freely on the Internet. Python is user-friendly programming software which has a large repository of packages.

Upon using the neural network toolbox from Matlab 8.1 a two layer feedforward network with sigmid hidden neurons and linear output neurons was created.

3.2 Objectives of the Study

1) To do an extensive literature review for methods of Bankruptcy Prediction.

2) To implement and test the efficiency and performance of one or more Machine learning techniques for bank bankruptcy prediction.

3) To identify factors which significantly impact the occurrence of Bankruptcy.

3.3 Data Collection

Primary data has not been used for the analysis of the study. The data has been obtained from research articles mentioned in the literature review. There are three bankruptcy datasets that are available and researched on widely they are first Spanish banks dataset which can be obtained from (FERNA´NDEZ, 1997). Second the Turkish banks dataset available in the website "(Anon., n.d.)" The third dataset is a qualitative bankruptcy dataset which can be obtained from the UCI machine learning repository.

3.4 Treatment of the data

The dataset of 66 banks has been split randomly into two sets. Set 1 comprising of 34 banks (15 failed and 19 non-failed) and set 2 of 32 banks (14 failed and 18 non-failed). The first set has been considered as the training dataset and the second set has been considered as the testing dataset. These have been used for the logistic regression method and for the decision tree method. The entire dataset of 66 banks has been considered when applying the neural network.

Some of the modules and libraries which were used as a part of the study in Python are Pandas, Numerical Python (NumPy), SciPy,Sklearn/Scikit-learn

3.5 Limitations of the study

There are three major limitations to study. The first limitation is with regards to selection of the banks for the study. The financial ratios of Spanish banks have been selected. The second limitation is with regards to the time period of the study. Since the study pertains to bankruptcy the time period when Spain faced a huge crisis has been selected. The third limitation, with regards to the quantitative methodology adopted in the study.

Though there are many qualitative aspects which would impact the bankruptcy of a bank they have not been considered in this study.

4 DATA ANALYSIS AND INTERPRETATION – FINDINGS OF THE STUDY

In this chapter the results of three models used to predict bankruptcy are stated. The three models are Logistic Regression, Decision Tree and XGBoost

The Spanish bank Data set has been taken from (FERNA´NDEZ, 1997). The data set consists of 66 banks 37 banks were bankrupt and the rest of them were solvent. Table 4-1 lists the ratios that are part of the data set.

Table 4-1Predictor Variables used in the study

Spanish Banks Data	
S.no	**Predictor Variable Name**
1	Current assets/total assets
2	Current assets-cash/total assets
3	Current assets/loans
4	Reserves/loans
5	Net income/total assets
6	Net income/total equity capital
7	Net income/loans
8	Cost of sales/sales
9	Cash flow/loans

The first three variables are **liquidity ratios**, while the fourth variable measures the **self-financing capacity of the bank**. The fifth, sixth and seventh ratios show the relationship of net income with total assets, total equity capital and loans. The eight ratio relates the **cost of sales to sales** and the ninth ratio relates the **Cash Flow of the bank to the debts.**

The **target variable** in this study is whether the bank is bankrupt or solvent. This is a **classification problem**.

4.1 Logistic Regression

The dataset of 66 banks was divided into two sets. The first set consisted of 34 banks, of which 19 are healthy and 15 were failed banks. The second set consisted of 32 banks of which 18 were healthy and 14 were failed banks. The first dataset was taken as a training data set and the second one was the testing dataset. The dataset consisted of the names of the banks, nine financial ratios and the class variable which described whether the bank had gone bankrupt or not. The class variable for a bankrupt bank was denoted as zero and that for healthy bank was denoted as one.

The concept of **regularisation** in machine learning helps prevent the model from over fitting the training sample. **Over fitting** in a model happens when the weights produce extremely good results on the training sample, but when provided with a new dataset have low accuracy levels.

In this model the logistic regression function is supplied with two arguments. The first being penalty which takes the values L1, L2. The second being the regularisation weights. The model is provided with the training data and also the classification of bankrupt and non-bankrupt banks. This step is followed by providing the testing data to the model. The resulting classification from the model is compared with actual values in the testing dataset. This is how we obtain the accuracy score. The model is provided with various combinations of penalty values and regularisation weights and each of them give a different accuracy score.

Since the data set is small the technique of cross validation has been adopted.One basic approach in cross validation is called Kfold method.. The study considered the case where the number of folds were equal to two. In this method the algorithm randomly splits the data into two sets. The first is used as a training set and the second as a testing set. After obtaining the accuracy score the two datasets are switched, the second dataset is used for training and the first dataset is used for testing.

The final accuracy score of the model is obtained by taking the average of the two accuracy scores obtained from the Kfold method.

Best Score and Model is: 0.8636

LogisticRegression(C=30, class_weight=None, dual=False, fit_intercept=True,intercept_scaling=1, penalty='l2', random_state=None, tol=0.0001)

4.2 Decision Tree

The Decision tree classifier has two criterion which are entropy and Gini. These are actually formulae which are used in the process of choosing the best split. The other arguments which this classifier takes are parameters such as maximum depth. .

4.2.1 Gini

Gini looks for the largest class in your database and strives to isolate it from all other classes. This rule would attempt to pull out the largest class into one node. This might not be possible for different sets of data, but, if it is, the Gini opts for that split. The same strategy is applied for the further nodes.

4.2.2 Entropy

Entropy is a way to measure the impurity in a given data set. Entropy comes from information theory, the higher the entropy the greater the information available for training.

In the training sample data provided, if we observe closely all except one instance have Ratio9 <0.0093. This happens to be the first condition developed by the Decision tree algorithm. Thus it is observed that the decision tree has correctly identified out of the nine ratios which plays the most significant role in determining the financial health of the bank.

4.3 Extreme Gradient Boosting

To predict regression and classification problem a machine learning technique called Gradient Boosting is used. This technique combines various weak prediction models to form an ensemble classifier.The XGB Classifier is supplied with two arguments which are the number of estimators and the learning rate.

```
clf=xgb.XGBClassifier(n_estimators=500,learning_rate=.02)
```

Results: -

The Prediction accuracy obtained by using this classifiers turned out to be **0.9065**

4.4 Feed Forward Neural Network

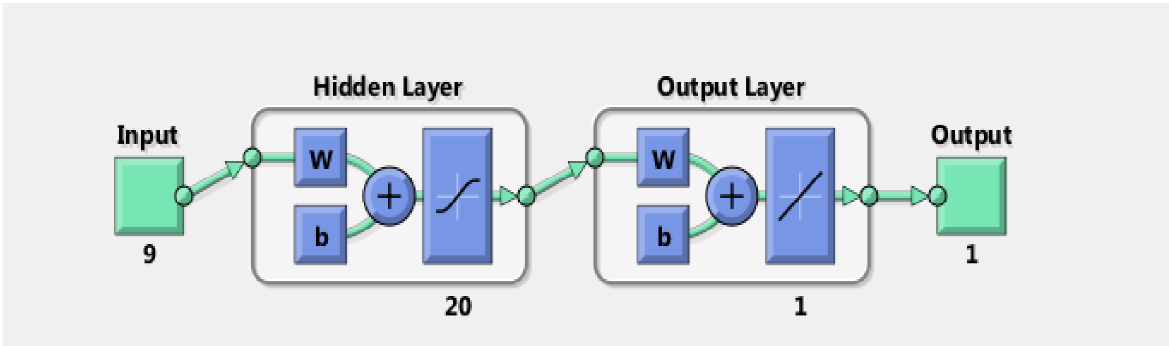
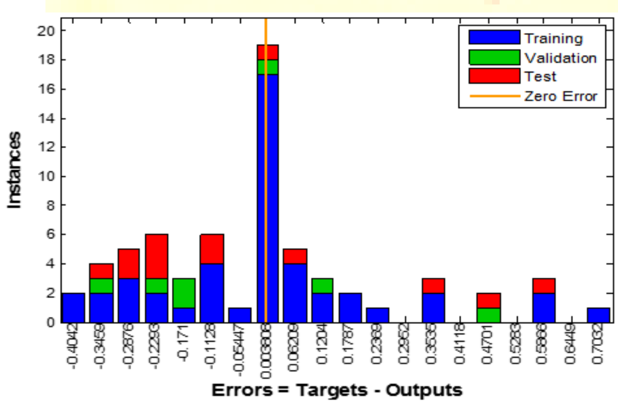


Figure 4-1Neural Network Architecture

A two layer feed forward neural network nine inputs and 20 hidden nodes was created as shown in Figure 4-1. Since the problem addressed was a classification case there was only a single output i.e. bankrupt or solvent. The algorithm used in this model was the Levenberg-Marquardt back propagation algorithm.

The Spanish banks data set which comprised of nine ratios of 66 banks were supplied to the network as 66X9 input matrix. The class variable was converted into numeric form where in bankrupt banks were labelled as zero and solvent banks as one. The class column which was 66X1 matrix was supplied to the model as the target data.The data set was divided into three parts training set – 70% (46 samples), validation set – 10% (7 samples) and testing set – 20% (13 samples). The next step is to select the number of neurons in the hidden layer. In this study twenty neurons have been selected in the hidden layer. This selection has been based on observing previous literature.The next step is to train the network, the training spontaneously



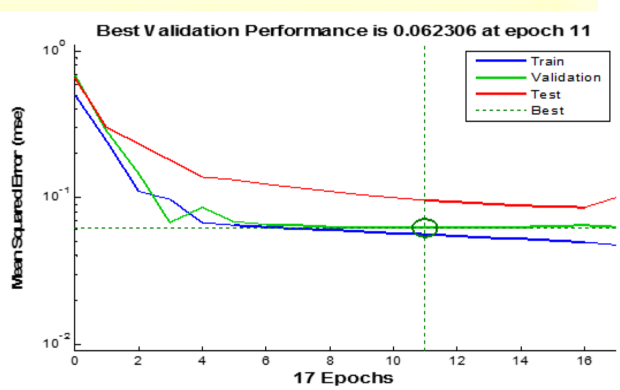


Figure 4-2Neural Network Training Error Histogram

Figure 4-3Neural Network training performance halts when generalisation stops refining. This is indicated by a rise in the mean square error of the validation samples. The best validation performance is 0.062306 at epoch 11 as shown in Figure 4-3. The Mean squared error is the averaged square difference between output and targets.

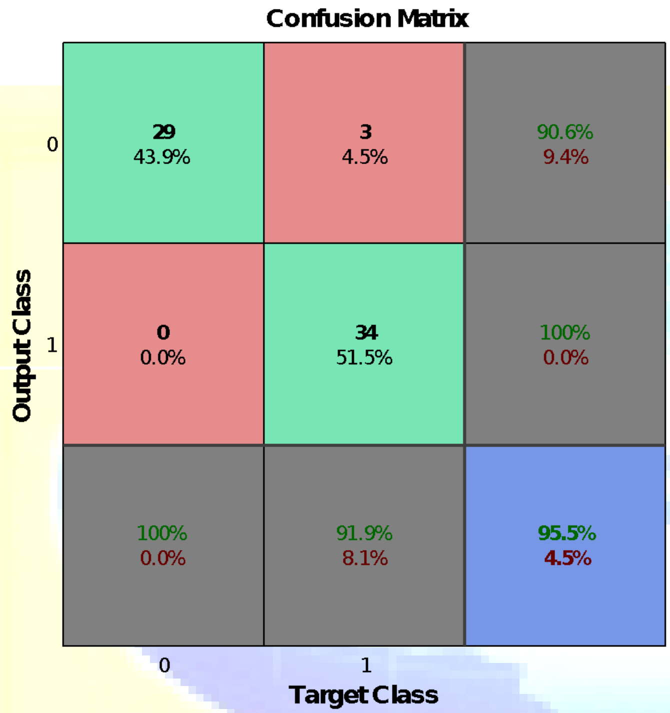


Figure 4-4Confusion Matrix for the Neural Network

Figure 4-4 shows the results using the confusion matrix. The values in diagonal cells in green colour show the number of cases correctly classified. The values in the off-diagonal cells show the misclassified cases. The blue cell shows the total percent of properly classified cases (in green) which is 95.5% and total percent of misclassified cases (in red) which is 4.5%

Table 4-2Comparative results of the various models

S.no	Algorithm	Accuracy obtained
1	Logistic Regression	86.36%
2	Decision Tree	81.25%
3	Extreme Gradient Boosting	90.65%
4	Feed Forward Network	95.5%

Thus we can conclude that for the Spanish banks data set the Feed-Forward Back Propagation Network has the maximum accuracy level of 95.5%

5 Conclusion

The objective of this study was to develop a model to predict bank bankruptcy. Four models are developed with varying levels of accuracy. The decision tree played an important role in identifying the ratio which has the highest significance in classifying a bank into the two categories which are bankrupt and solventThe decision tree provided accuracy level of 81%. The only statistical model among the four which is logistic regression provided accuracy of 86.36%. Another classifier used in this study was Extreme Gradient Boosting which gave a result of 90.625% Results showed that the two layer feed forward neural networks had the highest accuracy of 95.5% in classifying financially distressed banks in the Spanish banks dataset.

5.1 Scope for future work

In the study to model the contrasting approaches have been used. The decision tree algorithm uses the white box approach whereas the artificial neural network uses the black box approach. The first provides insight into the variables which affect the classification but has a low accuracy level. The second has a higher accuracy level but does not reveal information about the role of the ratios on the classification.

For future research one could consider using a hybrid model which has the advantages of both these approaches. The study has applied four models onto the Spanish dataset. Future studies could look at the Turkish banks dataset and apply these models. Other neural network architectures can be considered for improving the performance of the model. The study can consider datasets of larger sample size to improve the validity of the model.

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