Evaluation of various Bankruptcy Prediction Models

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Abstract

Bankruptcy Prediction Models plays a critical role in Loan Appraisal System for Banks and Financial Institutions across the globe. The study focuses on evaluation of various bankruptcy models available across literature. With plethora of choices among the models, it is interesting to evaluate various models with the perspective of end user and further construction of new models. History and evolution of Bankruptcy Prediction Models are discussed and evaluated. More than 50 Models from the US, UK, Greece, Cyrpus, India, etc. are studied since 1928. It is concluded out of 13 parameters to select the model; Transparency and Accuracy are of utmost importance to the end users. If Logistic Regression, Decision Tree Analysis, Multivariate Discriminant Analysis and Artificial Intelligence are used simultaneously then it can prove to be better in overcoming the weakness of Transparency and Accuracy.

Keywords

Bankruptcy Prediction Models, Artificial Neural Network, Logistic Regression.

Introduction

The lending has become very complex and bankers need to consider domestic and international markets in depth. The focus has been shifting from Balance Sheet to Cash Flow analysis for lending. Securitization of loans by banks and investment banks has standardize approach for evaluating credit risk. Also, with the increase its geographical reaches across the globe, bank need to have objective and standardize approach for evaluation. With the introduction of technology, modern lending techniques adopt sophisticated methodology to evaluate the probability of repayment and quantifying the risk. The major development has been in the field of credit rating, portfolio management, neural network and neural and intelligent knowledge-bases system. Two governing factors for lending are credit culture and credit standard. There has been a tremendous growth in the area of Credit Risk Evaluation; tools are broadly based from Statistics, Operations Research and Financial Market Based models. Statistics and Operations Research includes Survival Analysis, Neural Networks, Mathematical Programming, Deterministic and Probabilistic Simulation, Stochastic Calculus and Game Theory while Financial Markets based model includes Arbitrage Pricing Theory, Option Pricing Theory and Capital Asset Pricing Model. All these methods help the appraisal officers to predict whether the borrower will be able to repay or not. Monitoring performance after lending is even more critical, lending institutions are interested in prediction bankruptcy beforehand to take measures for further losses. Hence, Bankruptcy Prediction Models are very important aspect for any bank or Financial Institution. All of these were extensively studied, refined, tested if effective under various conditions and profitably implemented. These models need to undergo various constructs/variables; identify the variable and derive the relationship by using mathematics and statistics, simulation and other relevant technique to authenticate the relationship. Lastly, the models need to be tested upon and verified for outcome. In case of Credit Risk, models undergo the process which verifies the relationship through classification of the tools or techniques employed, the sector or the domain of application, and last the products on which the models shall be applicable[2].

There is a plethora of prediction models across the globe; it is developed considering various factors highly sensitive towards its background. The model construction is based on the data selection, tools/techniques, country, sector, etc. In an interesting interaction narrated in the article by Ajit Balakrishnan, founder Rediff.com quoted as “If you reject a consumer loan application and the consumer asks why her loan was rejected, you will get into regulatory trouble if you say, 'I don't know, the algorithm did it”. His expression brings a strong conviction on the requirement of transparency in the method of loan evaluation for the customer. It is highly desirable to include the transparency trait in selecting the right model[3].

History and Major Advancement of Bankruptcy Prediction Models

In 1928, Wall and Duning created the first example of real linear multivariate discriminant analysis through a ratio index, a weighted combination of several different ratios with the weights randomly selected to predict bankruptcy[4]. Later in 1932, Fitzpatrick investigated the differences between ratios of successful industrial enterprises with those of failed firms [5]. Smith and Winakor investigated the trends of twenty-one accounting ratios, analyzed the mean of each ratio up to ten years prior to the occurrence of the financial difficulty and concluded that the ratio of net working capital to total assets was the most accurate predictor of failure[6]. In 1942, nearly 1000 companies were analyzed spanning the period 1926-1936 by using ratios, viz., Current ratio, net worth to total debt, and net working capital to total assets[7]. Hickman found net profit to sales and the times-interest-earned ratios were the best predictors of default. In 1966, Beaver's model analyzed 79 failed companies between 1954 and 1964 by using 30 variables tested across 6 groups of financial ratios. A year before the bankruptcy was predicated 87% accurately and five year before at 78% by using Multivariate Discriminate Analysis (MDA) concluded single ratio known as best performing ratio Cash Flow/Total Debt Best Value[8]. From 1968 to 1980 was the era of multivariate discriminant analysis. In 1968, Edward Altman had come up with the now famous bankruptcy model known as Z-Score model. Altman's Z-Score model was introduced to incorporate the quality of ratio analysis as an analytical technique wherein a multiple discriminant statistical methodology was employed and set 5 ratios were introduced. The data of 66 companies equally distributed amongst bankrupt and non-bankrupt in the year 1964 were selected. With the use of Multivariate Discriminant Analysis (MDA) the accuracy results were 95%[9]. With the use of linear programming technique, a model was derived which was a useful tool for bank auditors, loan officers, and examiners with a meaningful measure of the loan portfolio's quality (Orgler, 1969).

Working further on Beaver's prediction model in 1972, Deakin extended the model by adding the element of probability and could produce better results. Total 14 Financial Ratios were selected for MDA technique to predict bankruptcy improved to 90% from 78% of Beaver's Prediction model before 2 years of bankruptcy[10]. In the same year, research focusing on the small business failure prediction used a dataset of 42 bankrupt companies which borrowed from

Small Business Association and Robert Morris Associates reduced the ratios to 7 through MDA technique. It could predict 39 out of 42 bankrupt firms with accuracy rate of 93%[11]. Total 230 companies both failed and non-failed used Failing Company Model (FCM) developed through MDA technique that quantify probability with accuracy rate of 93-95%,[12]. In 1977, Altman's model was criticized in terms of predictability and accuracy was presented[13].

The valuation of an asset is also a yardstick to predict the failure, a major breakthrough in the option valuation was presented in the public domain in 1973. One of the parameters of valuation lies in the discount of bonds based on the probability of default. In such a framework the default process of a company is driven by the value of the company's assets, and the risk of a firm's default is therefore explicitly linked to the variability of the firm's asset value[14,13,15], . Zavgren and Friedman used Logistic Regression for US based companies extracted from COMPUSTAT predicted bankruptcy using 7 financial variables. Prediction rate before 5 years of bankruptcy was just 12% while just before a year it was 98%[16]. The Hazard Model is preferred over static model theoretically; it corrects for period at risk and allows for time-varying covariates. It used financial ratios and converted to natural log, the results showed 95% accuracy in prediction[17]. By using 8 Financial Ratios of Bankrupt companies in Belgium used Logistic Regression Model resulted with 67% for business termination category and 91% for audit report model[18]. In an interesting study on comparison between sector focused and general prediction models, it was found that the Spanish companies general or unfocused prediction models are superior to focused (sector specific) models[19].

Discussion: Criteria for Bankruptcy Prediction Model

The quest to find a universal bankruptcy model will be really difficult due to variety of complications and factors involved in the data. Bankruptcy Prediction Model caters to different stakeholders considering their perspectives; lender will be interested in the accuracy of prediction while the company owner will be interested in knowing the transparency of the model. Total 13 criteria have been short listed for the evaluation; broadly divided as Results, Data and Tools Property[20]. The list of criteria is as follows:

1. Accuracy: prediction classification with minimum error, Type I and II.
2. Result transparency: Tool should be interpretable.

3. Deterministic: Tools must be able to classify the companies.
4. Sample size: The approximate sample size suitable to the tools to function optimally.
5. Data Dispersion: Tool's ability to compute equally or unequally dispersed data.
6. Variable selection: Variable selection method required for optimum results.
7. Multi-collinearity: It checks the sensitivity of the tool to deal with collinearity
8. Variable types: The tools capability to differentiate Quantitative and Qualitative variables.
9. Variable relationship: The tools capability to analyse linear and non-linear relationship.
10. Assumptions imposed by tools: Sample data has to satisfy for a tool to perform optimally.
11. Sample specificity/over-fitting: This is essential when the model is created by using one of the tools and it performs well on the sample but badly on validation of the data.
12. Updatability: Tool should be easy to update in case of any dynamic changes.
13. Integration capability: the ease with which the tool can be integrated with others for making it hybrid.

Approximate 50 research papers on Bankruptcy prediction were reviewed and the analysis of various models resulted in weighing the models on the prescribed variables mentioned above. Accuracy of each model is categorized from low to very high; MDA has the lowest while DT and LR are moderate and ANN has the highest accuracy. Transparency of results is high with LR and DT since LR explicitly shows the variables and its weight in the prediction model and DT diagrammatically shows the weight of variables. ANN, LR and MDA are deterministic while DT is non-deterministic; it means classification of companies is done with former models and not with DT. The quantum of data for prediction has to be generally large in size; it increases the probability of prediction since it considers variety of scenarios. None of the tools work well with small sizes. MDA and ANN have high ability to handle dispersed data while LR has normal but the same is not applicable to DT. The process of suitable variable selection is stepwise in MDA and LR while ANN and DT adopt case based method. Co-linearity amongst the variable is computed best in LR, then MDA followed by ANN and DT. The extreme cases/data where dispersion difference is too high is handled better by LR than MDA, ANN and DT. MDA requires quantitative data only while LR, ANN and DT can use both qualitative as well as quantitative data. MDA requires linear relationship amongst the variables; LR requires Logistic which means the results are dichotomous, ANN and DT can work on any kind of relationships the user wants to program. Liberty to incorporate assumptions in order to function optimally is well accommodated with MDA, lesser with LR and none with ANN and DT. If the model is developed on sample it should give desirable results on other data also, all the tools have been able to function properly on other data. This is most important of all since the model will be then replicated by the banking industry for lending decisions. The ease in updating the data with additional samples can be done with only ANN while rest does not support this function effectively. For creating hybrid model; ANN and DT can work effectively but not MDA and LR. The decision or the results reflected by some cut-off points or probabilities in MDA, LR and ANN are in binary while DT provides the Decision Rule.

	Important criteria	**Tools**			
		MDA	*LR*	*ANN*	*DT*
1	Accuracy	Low	Mod.	V. High	Mod.
2	Result transparency	Low	High	Low	High
3	Can be Non-deterministic	No	No	No	Yes
4	Ability to use small Samples size	Low	Low	Low	low
5	Data dispersion sensitivity	High	Normal	High	NR
6	Suitable variable selection	SW	SW	Any	Any
7	Multi-collinearity Sensitivity	High	V. High	Low	Low
8	Sensitivity to outlier	Mod.	High	Mod.	Mod.
9	Variable type used	QN	Both	QN (both)	(both)
10	Variable relationship required	Linear	Logistic	Any	Any
11	Other Assumptions to be satisfied	Many	Some	None	None
12	Over-fitting possibility	Yes	Yes	Yes	Yes
13	Updatability	Poor	Poor	OK	Poor
14	Ways to integrate to give hybrid	Few	Few	Many	Many
15	Output Mode	Cut-off	Binary	Binary	DR

NR: Not Reported SW: Stepwise V.: Very Mod: moderate QN: Quantitative QL: Qualitative DR: Decision rules.

Table 1 : Evaluation of Bankruptcy Prediction Models-Multivariate Discriminant Analysis (MDA), Logistic Regression (LR), Artificial Neural Network (ANN) and Decision Tree (DT) Adapted version[20]

The combination of all the four would overcome the weakness of each other; based on various factors evaluated Accuracy and Transparency are most diverse and critical from the view point of the end user, hence model selection must stress upon these factors.

Debate and Comparison of Bankruptcy Prediction Models

The following discussion is based on using various techniques to find better method in various countries and industries. Z-Score method has been very popular across the world, to test the accuracy of model, parameters of Z-Score were used Artificial Neural Network techniques resulted in better accuracy than MDA; ANN resulted 90% and MDA with 85% accuracy rate for US companies[21]. Similarly, an attempt to find the bankruptcy risk for Greek banks used a hybrid method of Rough Sets to predict the risk of insolvency used many financial ratios and qualitative data like years of experience of the bank managers, errors of management, firm's market position, and special competitive advantage claimed to be functioning well with Greek Banks[22]. In a comparative study of various bankruptcy prediction models for Korean companies, viz., Case Based Reasoning, MDA and ANN, 51 financial ratios across 6 industries were used resulting in accuracy ranging between 81 and 83% in all the methods; ANN with 82.98%, MDA at 82.43% and Case Based Reasoning at 81.88%[23]. A study on model comparison of 1139 banks in all the regions of the USA used ANN, Logit and MDA for 3 years prior to the bankruptcy resulting in ANN with better accuracy and lesser cost in comparison to other methods[24]. Various branches of computer programming based methods became famous amongst the financial fraternity and grabbed the attention of Computer Science, Financial and Banking sectors. Support Vector Machine method was used for 1160 bankrupt and non-bankrupt Korean companies each with 10 financial ratios as the variables. The method of optimizing was used to discover where SVM has the highest level of accuracies and better generalization performance than BPN as the training set size was getting smaller sets. Overall accuracy was more than 73% at the optimum level[25]. As discussed above, prediction models, in a study covering all non-finance industry UK firms fully listed on the London Stock Exchange (LSE) at any time during the period 1985-2001 with a sample size of 2,006 firms, a total of 15,384 firm years, and 103 failures, used prominent models, viz., Z-Score, Hillegeist Models and Bharat Schumway Model. Z-Score had the best result with 89% accuracy followed by Bharat Schumway with 87% and Hillegeist with 84%[26]. For bankruptcy prediction with respect to Turkish Banks, a sample of 65 failed banks and 130 non failed entities was selected with 20 variables including that of CAMEL analysis, capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk.

The study used 2 methods to predict the failure: Neural Network and Multivariate Statistical methods; in the case of neural networks, four different architectures namely multi-layer perceptron, competitive learning, self-organizing map and learning vector quantization are employed while multivariate statistical methods; multivariate discriminant analysis, cluster analysis and logistic regression analysis tested. Learning vector quantization (LVQ) resulted in a phenomenal result of 100% accuracy followed by Multi-Layer Perceptron with 95% and Support Vector Machines (SVM) with 91% accuracy[27].

In yet another attempt to find the better technique for bankruptcy prediction, 32 bankrupt and 45 non-bankrupt companies in England comprised the sample. Variables selected are ratios regarding Management Inefficiency, Capital Structure, Insolvency, Adverse Economic conditions and Income Volatility for the Logit model and the quadratic interval logit model, Multi Layered Perceptron and Radial basis Function Network resulted in the accuracy ranging from 91.5% to 77.05% where the best method is Radial Basis Function Network[28]. Considering the Decision Tree models for bankruptcy predictions, 200 US companies with 142 non-bankrupt and 58 bankrupt companies were selected to fit in Recursive Partitioning Analysis (RPA), Multivariate Discriminant Analysis and CART. RPA and CART has provided best results of accuracy as compared to other methods[29]. In an exhaustive study on Neural Network techniques for bankruptcy prediction, more than 200 researches on bankruptcy prediction were analyzed since 1964. It was found that the most predominant techniques are discriminant analysis, logistic regression and multi-layer perceptron neural network. The research data consisted of 260 bankrupt and healthy French companies respectively. The idea was to shortlist the variable to be used for the bankruptcy prediction model; 41 variables in total were considered the important variables. NN is the best of all with an accuracy of 92.32% while MDA with 84% and Logistic Regression with 89%[30]. For 887 bankrupt companies in the US from 1980-2006, compared Altman, Ohlson, Zmijewiski, Shumway, and Hillegeist models resulted as Ohlson being the best followed by Zmijewski, Hillegeist, Shumway and lastly Altman. In a new proposed model, most of the variables from the above mentioned model were used comprehensively provided best results with accuracy of 89%[31].

A total of 562 bankrupt Slovenian companies were studied on 64 financial variables by using the Decision Tree technique, CART. For estimation, 75% of the variables were used and the remaining for the test. The accuracy rate stood at 94.6%[32]. In Iranian companies, logistic regression model provided 88.8% accuracy[33]. A study on bankruptcy models for UK companies used 18589 company-years and selected 12 variables covering accounting, market and macro economy. Three methods were tested upon; NN, Altman's Z Score and Logistic Regression. NN had the maximum accuracy of 84.7%, Altman's with only 65% and Logistic Regression with 84%[34].

A study on bankruptcy prediction involving Russian companies were worked upon for Bankruptcy prediction on the data size of 3505 company years Bankrupt and 3104 Non Bankrupt company year. It used 98 unique ratios across various parameters including Cash Flow, Liquidity, Profitability, Turnover, Balance Structure, indicators from previously constructed models and Russian Legislations to compute by using LR, MDA, ANN and Classification and Regression Tree (CRT). A unique method of combining various models was decided on the basis of significance, intersection and CRT+LR. The basis of intersection by using ANN provided best results with an accuracy of 88.8% while MDA, CRT and LR resulted in accuracies of 74.5%, 86.7% and 87.8% respectively[35]. In an extension to the study on bankruptcy prediction models by Phillippe Jardin, further focuses on retail, construction and service sectors in France from 2005-2010 with 50 financial ratios. The failure prediction 1, 2 and 3 years prior to default computed by using a new failure based model to compute LR, Cox model, MDA and ANN techniques. Accuracy rate was ranging from 75 to 85 % across the period. Failure based model provided best results in predicting accuracy 3 years before the default for all the years for all the techniques. However, average accuracy rate for all the methods was 80%[36]. A study on 250 companies, including 107 bankrupt ones, for which data were obtained from a Korean bank with 107 Bankrupt companies, used 6 major heads of financial ratios to decide how MDA, SVM and LR methods can predict accurately. With 94.55% accuracy, SVM was the best and MDA at around 93% and LR with 92% predictions[37]. For the bankrupt companies in Pakistan, a sample pool of 422 bankrupt companies used Altman's Z-score, Ohlson's O-score, Zmijewski Model, Shumway Model and Blums model resulted in overall accuracy of 66%, 68%, 70%, 73% and 42.8% respectively[38].

For India, 1460 listed companies were taken as sample to test Altman's, Zmijemski's, Springate's and IN05 models. It was further computed using Decision Tree model where the accuracy rate was a meager 54.6% and ANN was just 43%[39]. Prior to this, from 2002-2016 a research study focusing on Wilful Default used total 558 sample companies with equal number of bankrupt and non-bankrupt, 279 in each category used logistic regression and resulted in overall 87.5% accuracy[40]. In the quest to develop a bankruptcy model for Cyprus based companies, 318 companies out of which 73 were bankrupt used financial ratios of the non-financial listed companies with the help of Logistic Regression resulted in 91.2% accuracy in the results[41].

On the basis of the preceding literature review, bankruptcy prediction models have been summarized on the basis of the country, variables used and accuracy rate of various techniques in Table 2.

Year	Author	Variables	Country	Method/Accuracy										
				LR	**DT**	**MDA**	**ANN**	**Z Score**	**CBR**	**SVM**	**Schumway**	**Heillegiest**	**Ohlson**	**Zmijewski**
1966	Beaver	Financial Ratio-30	US			87								
1968	Altman	Financial Ratio -5	US			95								
1972	Deakin	Financial Ratio -14	US			90								
1972	Edmister	Financial Ratio -7	US			93								
1974	Blum	Financial Ratio -12	US			93-95								
1980	Ohlson, James	Financial Ratio -10, Macroeconomic-1	US		96.3									
1988	Zavgren,	Financial	US	98										

	Freidman	Ratio -7												
1994	Rick L. Wilson and Ramesh Sharda	Altman-5 Variables	US			85	90							
1995	R. Slowinski and C. Zopounidis		Greece											
1997	Hongkyu Jot And Ingoo Han Hoonyoung Lee		Korea			82.43	82.98		81.88					
1997	Harlan L. Etheridge1 and Ram S. Sriram		USA				Better							
2001	Shumway	Financial Ratio -5	US	95										
2005	Kyung-Shik Shin*, Taik Soo Lee1 , Hyun-jung Kim2	10 financial ratios	Korea							73				
2006	Vineet Agarwala and Richard Tafflerb*		UK					89			87	84		

2009	Melek Acar Boyacioglua Yakup Karab Ömer Kaan Baykanc	CAMEL Analysis Variables	Turkey				100			91				
2010	Fang-MeiTsenga Yi-ChungHub	Financial, macro economic	UK	77.05			91.5							
2010	Adrian Gepp, Kuldeep Kumar, Sukanto Bhattacharya		USA											
2010	Philippe du Jardin	Financial Ratio -41	France	89		84	92.32							
2010	Wu, Gaunt, & Gray	Models- Altman, Ohlson Zmijewski, Shumway, Hillegiest	US	89				28			73.96	75.24	79.7	78.54
2012	Arjana Brezigar-	Financial	US		94.6-									

	Masten, Igor Masten	Ratio -64			CART									
2012	Akbar Pourreza Soltan Ahmadi, Behzad Soleimani, Seyed Hesam Vaghfi and Mohammad Baradar Salimi	Financial ratios	Iran	88.8										
2012	Gaeremynck & Willekens	Financial Ratio -7	Belgium	90										
2013	Bagher Asgarnezhad Nouri1 , Milad Soltani2	Financial Ratio	Cyprus	91.2										
2013	Mario Hernandez Tinoco, Nick Wilson	Financial Ratio, market and macro economy-12	UK	84			84.7	65						
2013	Elena Fedorova,	Financial	Russia	87.8	86.7	74.5	88.8							

	Evgenii Gilenko, Sergey Dovzhenko	Ratio -98												
2014	Philippe du Jardin	Financial Ratio -50	France	80.5		80.15	80.9							
2015	Lawrence, Pongsatat, & Lawerence	Financial Ratio-Macroeconomics	Thailand										<90	
2017	Hafiz A. Alakaa , Lukumon O. Oyedele, Hakeem A. Owolabi , Vikas Kumar, Saheed O. Ajayi, Olugbenga O. Akinadef, Muhammad Bilal	NA												
2017	Vicente García, Ana I. Marqués,	6 Category of Financial	Korea	92		93				94.5				

	J. Salvador Sánchez, Humberto J. Ochoa-Domínguez	Ratio												
2018	Karthik, Lakshmi; Subramanyam, M.; Shrivastava, Arvind; Joshi, A. R.	Financial Ratio -9	India	87.5										
2019	Ashraf, Felix, & Serrasqueiro	Models-Altman, Zmijewski, Ohlson, Shumway, Blum	Pakistan					66			73		68	70

Table 2: Review of Bankruptcy Prediction Models based on Accuracy rate (%)

Research Gaps

After an extensive survey of literature, few areas are identified which requires attention, there has been limited research in the field of Wilful Default in India. New models focusing on Wilful Default, that is, deliberately going bankrupt by unfair means can be constructed that can suit the condition of Indian conditions.

Conclusion

Bankruptcy Prediction Models across the world studied and found to be very dynamic in nature. Multiple factors are considered in selecting models and its applicability. The techniques like accounting ratio, econometric techniques, Expert systems, hybrid systems and Artificial Intelligence have been used so far for different countries like the US, UK, Spain, Belgium, France, Greece, Korea, India, etc. by using 50 different bankruptcy models across 15 countries were studied and following points were observed.

1. Notably, major 4 techniques are widely used; Logistic Regression since it brings out dichotomous results whether the company will default or not, Multivariate Discriminant Analysis which includes all major affecting variables and provides a binary answer, Decision Tree provides a pictorial presentation of the weight of variables and Artificial Neural Network which has been predominantly used in many cases with best results compared to others.
2. Variables used are mostly Financial Ratios of the companies and few were macro economic variables to factor in the impact of business cycle (Boyacioglu, Kara, & Bayken, 2009) (Feng, Shaonan, Chihoon, & Ling, 2019) (Ohlson, 1980).
3. Initially LR was used while later in 1960 MDA became more popular and few prominent models like Altman's Z Score Model, Ohlson's O Score Model, Zavgren Model, Zmisjewski Model, etc. were constructed. After 1990, ANN technique was widely used with various versions and models like Support Vector Machines, Rough Sets, Case Based Reasoning, Decision Tree and Genetic Algorithm.

4. The tools are evaluated mainly on the basis of transparency in the process and most importantly; accuracy of the models. LR and MDA have the maximum transparency of the process as compared to other like ANN, DT, SVM, etc. However, in terms of accuracy; ANN and related techniques provides the best results as compared to LR and MDA.
5. Results of various bankruptcy models can be categorized in terms of accuracy. When one wants to deal with the systemic problem; accuracy of the models is of vital importance. Based on the survey of literature it concludes the ANN has an average accuracy rate of almost 90% ranging from 80 to 100% in different set ups followed by LR with around 87% and MDA with 86% average accuracy rates.
6. There is ample literature available based on existing models like Altman, Ohlson, Zmijewski, Schumway, Heillgeist, etc. which have been incorporated to test the accuracy of these models in various conditions like time period, country and the sample size. Testing has been done for US, UK, Iran, India, Thailand and Pakistan results in accuracy ranging from 60% to 80%.

Future Direction

As identified in the Research gap, it will be a good forward path to consider these models in Indian condition and construct a new model after considering the evaluation of Bankruptcy Prediction Models with special reference to Wilful Default.

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