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Application of Artificial Neural Network to Predict Wilful Default for Commercial Banks in India

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Abstract

Since 2014, the problem of the rise of Non-Performing Assets (NPA) in the Indian banking system has been a subject of investigation. A major impact of mounting NPA has tested the bank's ability to recover bad loans and its capacity to lend in the short run. Among others, wilful default has been a significant category of NPA; it is detrimental to the financial health of the banking system. The share of wilful default in the total NPA for the year 2018 stands at 44%. By and large, wilful default indicates 'intend of fraud'. As declared by various banks, around 106 companies are identified as wilful default companies from those listed between 2000 and 2018. The research paper constructs a model to predict the wilful default using an artificial neural network. The model is based on 106 wilful default companies and 106 non-default companies. The model predicts an accuracy rate of 92.2% and the variables with the highest degree of importance are found to be Profit before Interest and Taxes/Total Assets, followed by Enterprise Value/Total Assets, Operating Profit Margin, Cash Flow Financing/Cash Flow Investing, Total Debt/Total Asset, Sales/Capital Employed, Retained Earnings/Total Assets, Return on Shareholders' Funds, PBIT/Sales, and others.

Keywords: Artificial Neural Network, Wilful Default, Non-Performing Assets, Bankruptcy Prediction Model

Introduction

As per RBI's Master Circular on wilful defaulter, a "wilful default" is deemed to have occurred if any of the following events is noted. When the unit has:

- Capacity to repay but still defaulted in meeting its repayment.
- Diverted the funds for purposes other than specified in the loan terms.
- Siphoned off the funds, that is, the funds are neither used in buying assets specified in the loan terms nor other assets.
- Disposed of or removed the movable fixed assets or immovable property given by the borrower to secure a term loan without the knowledge of the bank/lender. (RBI, Master Circular, 2014) (RBI, NOTIFICATIONS-Master Circular on Wilful Defaulters, 2015).

Among other measures that can be taken to moderate the risk of default, a centralised information infrastructure plays a significant role for banks to appraise lending. With the introduction of credit information companies, India is moving towards better lending space. The cases are reported in public by the lender through credit information companies (CIC) like Experian Credit Information Company of India Private Limited, Equifax Credit Information Services Private Limited, CRIF High Mark Credit Information Services Private Limited, and Credit Information Bureau (India) Limited (CIBIL). It provides details, quarterly, from both banks and financial institutions. In 2019, RBI launched a new web-based Central Information System for Banking Infrastructure (CISBI). These initiatives and efforts using digital information will simplify data sharing in the Indian banking system, leading to better coordination among banks and monitoring authorities.

The magnitude of wilful default data about non-performing assets justifies the scope of the study.

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Table 1: Bank Group-Wise Gross Non-Performing Assets, Gross Advances, and Gross NPA Ratios of Scheduled Commercial Banks 2018

Banks	Gross NPAs (Rs. Billion)	% Gross NPA of Total	Gross Advances (Rs. Billion)	% Gross Advances of Total	Gross NPAs to Gross Advances Ratio (%)
1	2	3	4	5	6
Nationalised	8956.01	86.43	61416.98	66.53	14.58
Private Sector	1258.63	12.15	27258.90	29.53	4.61
Foreign	13830	1.33	3633.04	3.94	3.81
Small Finance	8.93	0.09	353.16.	0.38	2.53
Total	10361.87	100	92308.94	100	11.18

Source: Department of Supervision, Reserve Bank of India

As per Table 1, RBI claims that with 86.43% of GNPA and 14.58% of GNPA to Lending Ratio, the financial health of public sector banks is dismal, followed by private sector and foreign banks in India.

Data on wilful default as presented in Table 2, as of 31 March 2018, will help us consider the problem in its severity. The table includes the wilful default number of cases classified as accounts wilful with more than Rs. 1 crore and more than Rs. 25 lakhs. A comparison among schedule commercial banks, nationalised, private sector, and foreign banks indicates the dominance of public sector banks in hosting wilful default accounts.

Table 2: Suit-Filed Accounts-Wilful Default as on 31 March 18 Summary (Column 2 and 5 in Rs. Billion)

Banks	More than Rs. 1 Crore (Amount)	Share of Total (%)	No. of Cases	Rs. 25 Lakhs and Above (Amount)	Share of Total (%)	No. of Cases
1	2	3	4	5	6	7
Nationalised	2543.92	80.58	15284	1125.95	87.51	8058
Private Sector	500.66	15.86	2964	152.19	11.83	1399
Foreign	112.33	3.56	390	846.80	0.66	43
Total	3156.92	100	18638	1286.62	100.00	9500
Grand Total	4443.53					

Source: Transunion and Cibil

With reference to Tables 1 and 2, more than 40% of the total NPA of Rs. 10 trillion falls under the category of wilful default. Public sector bank have the maximum share of not only NPA, but also wilful default. Interestingly, wilful defaults increased dramatically by 78% from 2017 to 2018, amounting to Rs. 44 trillion from the earlier Rs. 25 trillion.

The problem of wilful default is a serious cause for concern of the overall health of the banking system. Hence, an attempt to predict wilful default in advance can be of great help. With technological advancement and awareness, use of Artificial Intelligence (AI) in solving serious economic problems specific to big data is gaining impetus. It would not be wrong to comment that AI is the 'Future of Banking'. A process-driven AI, along with the advanced level of data analytics in the banking industry, can be a boon to identify and restrict fraudulent transactions. In addition, AI will play an important role in enhancing compliances in the banking industry, by managing large volumes of data and information, process them speedily, and share the information among all the stakeholders for efficient decision-making, including credit lending.

Review of Literature

NPL (non-performing loan) or NPA are those loans in which interest (or principal) is overdue by 90 days (RBI, Master Circulars, 2001). The NPA-qualifying definition may vary a bit in the US, UK, Japan, Korea, Taiwan, China, or any other country (Golin & Delhaise, 2013) (Khan, 2009) (Bloem & Freeman, 2005) (Inaba, Kozu, & Sekine, 2017) (Bank C. C., 2004) (Bank H. S., 2015) (Taiwan, 2014) (Bholat, Lastra, Markose, Miglionico & Sen, 2016).

It is significantly important to study the nature and causes of NPA as it is an important key performance indicator of the banking system, especially related to safety and soundness (Throsten & Cull, 2005) (Lin & Zhang, 2009) (Siraj & Pillai, 2013). A significant branch of research stresses the central role of assets quality as a predictor of bank failures (Berger, 1997) (Abdelkader, Boulila Taktak & Jellouli, 2009). Apart from endogenous and exogenous factors, the impact of banking regulation and poor supervision can be one of the major causes of NPA (Abdelkader, Boulila Taktak & Jellouli, 2009) (Barth, Caprio & Levine, 2004).

The bank contemplates the entire risk exposure at the international and national level through the central bank and Basel Norms. The comprehensive set of risk includes operational, currency, interest rate, market, and credit risks. A bank is exposed to multiple risks just in one profile of the prospective borrower (Rousse, 2002). For mitigating and identifying credit risk, prediction models undergo a process which verifies the relationship through the classification of the tools or techniques employed, the sector or the domain of application, and lastly, the products on which the models shall be applicable. The most commonly used technique is from econometrics, neural networks, optimisation models, rule-based, or expert and hybrid systems (Caouette, Altman, Narayanan & Nimmo, 2008).

Artificial Neural Network (ANN) is a computer-programming-based model and works on the same lines as a human brain (Bishop, 1995). It is interconnected with many algorithms set up through econometric models. It provides flexibility in building a non-linear association between the dependent and independent variables. One of the types of ANN, viz., multilayer perceptron (MLP), consists of three layers: inner, hidden, and outer. Each layer is connected to the other and the interconnection is very strong; it works as a wire mesh to transmit the information and calculate it further (Brown, 2014). This technology helps in higher iterations and minimal error in the outcome. Accuracy comparison with various bankruptcy prediction models, like traditional techniques, and linear and logistic regression, finds ANN and Genetic Programming from Advance tool is consistently accurate in prediction. “Early warning system” with probability-based neural networks using Bayes’ classification theory was developed thereafter (Yang, 2001). A set of data tested on small Italian businesses by using ANN showed positive results in prediction. Two ANN models were developed in the research; one with Standard Feedforward Network and the other with special Architecture (Angelini, Tollo, & Roli, 2008). Another interesting research based on the experimental method suggested that both emotional and neural network can be used effectively for evaluating credit risk. However, emotional models outperformed in terms of speed and accuracy of decision making (Khashman, 2011).

For the application of artificial neural network, parameters of Z-Score, one of the widely used bankruptcy prediction models, were used. Artificial neural network techniques resulted in better accuracy than MDA. ANN resulted in 90% and MDA in 85% accuracy rate for the USA companies (Wilson & Sharda, 1994). In a comparative study of various bankruptcy prediction models for Korean companies, viz., case-based reasoning, MDA, and ANN, 51 financial ratios across six 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% (Jot, Han & Lee, 1997). A study on model comparison of 1,139 banks in all the regions of the USA used ANN, Logit, and MDA for three years before the bankruptcy resulting from ANN had better accuracy and cost less in comparison to other methods (Etheridge & Sriram, 1997). Various branches of computer-programming-based methods became famous among the financial fraternity and grabbed the attention of the computer science, financial, and banking sectors. Support Vector Machine (SVM) method was used for 1,160 bankrupt and non-bankrupt Korean companies, each with ten financial ratios as the variables. The method of optimising was used to discover where SVM has the highest level of accuracies and better generalisation performance than Back-Propogation Neural Network as the training set size was becoming smaller. Overall accuracy was more than 73% at the optimum level

(Shin, Lee & Kim, 2005). The study used two 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-organising map, and learning vector quantisation were employed, while in multivariate statistical methods, multivariate discriminant analysis, cluster analysis, and logistic regression analysis were tested. Learning vector quantisation (LVQ) resulted in a phenomenal 100% accuracy, followed by multi-layer perceptron with 95% and support vector machines (SVM) with 91% accuracy (Boyacioglu, Kara & Bayken, 2009).

In yet another attempt to find a better technique for bankruptcy prediction, 32 bankrupt and 45 non-bankrupt companies in England comprised the sample with 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 an accuracy ranging from 91.5% to 77.05%, where the best method was proved to be radial basis function network (Tseng & Hu, 2010). A study on bankruptcy models for UK companies used 18,589 company-years and selected 12 variables covering accounting, market, and macroeconomy. Three methods were tested: ANN, Altman's Z-Score, and logistic regression. ANN had the maximum accuracy of 84.7%, Altman's only 65%, and logistic regression 84% (Tinoco & Wilson, 2013).

By using 98 unique ratios across various parameters, including cash flow, liquidity, profitability, turnover, balance structure, indicators from previously constructed models and Russian Legislations to compute using LR, MDA, ANN, and Classification and Regression Tree (CRT). A unique method of combining various models was decided based on significance, intersection, and CRT+LR. The basis of intersection by using ANN provided the 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 (Fedorova, Gilenko, & Dovzhenko, 2013). An extension to the study on bankruptcy prediction models by Phillippe Jardin focuses on retail, construction, and service sectors in France from 2005-2010, with 50 financial ratios. The failure prediction one, two, and three years before default was computed using a new failure-based model to compute LR, Cox model, MDA, and ANN techniques. The accuracy rate ranged from 75 to 85% across the period. The failure-based model provided the best results in predicting accuracy three years before the default for all the years for all the techniques. However, the average accuracy rate for all the methods was 80% (Jardin, 2014).

In the Indian context, the study on wilful default is limited; it includes research from 2002-2016 focusing on wilful default, which used a total of 558 sample companies with an equal number of bankrupt and non-bankrupt firms, 279 in each category used logistic regression and resulted in an overall accuracy of 87.5% (Karthik, Subramanyam, Shrivastava & Joshi, 2018). Concerning artificial neural network, 1,460 listed companies were taken as a sample to test Altman's, Zmijemski's, Springate's, and IN05 models. It was further computed using the decision-tree model, where the accuracy rate was a meager 54.6% and ANN was just 43% (Kapil & Agarwal, 2019).

The review from literature across countries like the US, UK, Korea, Italy, India, and France indicates that artificial neural network has been used widely. It concludes that the accuracy rate has maximum ANN in most cases. In addition, it indicates a gap in research in the Indian context, especially in wilful default.

Objective

To construct bankruptcy prediction models for wilful default public limited companies listed from the year 2000 by using artificial neural network.

Research Methodology

The research is categorised as analytical. The research is based on the financial performance data of the companies. It critically examines and tries to draw a relationship among the variables. It is primarily a statistical compilation and follows many computations. It is applied research since it focuses on banking business-related problems. The entire research is quantitative; it takes only the financial performance data. It is further classified as empirical research since it is based on past data (*post ante*). The approach is deductive, where conclusions are drawn using various statistical techniques.

Over 900 IPOs were launched between 2000 and 2017, out of which 106 have been declared as wilful defaulters.

These 106 companies constitute the entire population of the study. Further, non-default companies of equal number, that is, 106, are shortlisted based on the highest market capitalisation in India.

Population: It comprises all the public limited listed companies in India. There are more than 5,000 listed companies.

Sampling Unit: It considers the public limited listed companies listed after 2000 till 2018, which comprises around 900 companies.

Sampling Method: The method of sampling is purposive as the sample selected is based on the pre-decided defined objective.

Size of Sample: The entire population of the defined scope is 106 public limited wilful default companies. In addition, for model creation, the top 106 companies from BSE 200 index are shortlisted based on their market capitalisation, excluding the companies in the banking and financial sectors.

Parameters of Interest: Financial performance from 2000 to 2018 in the years falling relevant for the companies covers the following parameters.

Table 3: Variables-Ratios

1	Liquidity Ratios
1.1	Current Ratio
1.2	Net Working Capital/Total Assets
2	Profitability Ratios
2.1	Net Profit Margin
2.2	Operating Profit Margin
2.3	PBIT Margin
2.4	Return on Assets
2.5	Return on Shareholders' Fund
2.6	Return on Capital Employed
3	Solvency and Valuation Ratios
3.1	Interest Service Coverage Ratio
3.2	Total Debt/Total Assets
3.3	Retained Earnings/Total Assets
3.4	EBIT/Total Assets
3.5	Sales/Total Assets
3.6	Debt/Enterprise Value
3.7	Profit After Tax/Enterprise Value
3.8	Enterprise Value/Total Assets
4	Cash flow Ratios
4.1	Increase (Decrease) Loan Funds/Cash-flow from Loan
4.2	Cash-flow Financing/Cash-flow Investing
5	Miscellaneous
5.1	Market Capitalisation/Outstanding Debt
5.2	Sales/Capital Employed
5.3	Minority Interest/PAT

Collecting the Data: The data is extracted from the Software Ace Equity powered by Accord FinTech. The statistical computations are on IBM SPSS and Microsoft Excel.

Data Size: Table 4 shows the details of the research data computed.

Table 4: Details of Data Selection

Sr. No.	*Parameter*	*Total Observations*
1	Total Companies	106+106 = 212 (Default and Non-Default)
2	Number of Years	18 (2000-2018)
3	Number of Years and Companies (Company Years)	3,319
4	Total Parameters	21 (Financial Ratios)
5	Wilful Default–Years and Parameters	28917
6	Non-Default–Years and Parameters	40782
7	All Companies, All Years, All Parameters	69699

Variable consists of five categories of financial ratios: liquidity, profitability, solvency, valuation, cash flow, and miscellaneous. A total of 21 financial ratios from five categories have been considered for the construction of ANN models.

Using the above-stated methodology, all the data has been extracted from Ace Equity Software and computed on IBM SPSS. The analysis and results are discussed below.

ANN Model Building

An artificial neural network is an attempt to replicate the brain's neural network. It has been used extensively for programming Artificial Intelligence Softwares. As per the literature review, this method has the highest accuracy rate. The data is studied using IBM SPSS software to construct the ANN model. The model is processed under multi-layer perceptron (MLP), a class of feed-forward ANN. The model is built through various steps, starting with the processing of data. It divides the data in the ratio of 70:30, where 70% is training and 30% is testing data (Table 5). After various simulations on 70% of the data, the same is tested on the remaining 30% to provide the importance of variables. It provides the outcome in terms of accuracy (Classification-Table 8).

From Table 5 on Case Processing, 2161 was taken as training input and 962 as testing input to process the data.

Table 5: Case Processing Summary

		N	*Percent*
Sample	Training	2161	69.2%
	Testing	962	30.8%
Valid		3123	100.0%
Excluded		196	
Total		3319	

ANN is constructed using a single hidden layer, where the input layer consists of 21 variables and its hidden layer six units. For the hidden layer, the Activation function is a hyperbolic tangent and the output layers are two units (default and not) with activation function Softmax.

Table 6: Network Information

Input Layer	Covariates	1	Current Ratio
		2	Net Profit Margin
		3	Operating Profit Margin
		4	PBIT Margin
		5	Return on Assets
		6	Return on Shareholders' Fund
		7	Return on Capital Employed
		8	Interest Service Coverage Ratio
		9	Net Working Capital/Total Assets
		10	Retained Earnings/Total Assets
		11	PBIT/Total Assets
		12	Market Capitalisation/BV of Total Debt
		13	Sales/Total Assets
		14	Inc Dec Loan Funds/CF from Loan
		15	Sales/Capital Employed
		16	Total Debt/Total Assets
		17	CF Financing/CF Investing
		18	Minority Interest/PAT
		19	Debt/EV
		20	PAT/EV
		21	EV/Total Assets
	Number of Units		21
	Rescaling Method for Covariates		Standardised
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		6
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	DEFAULT
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy

Excluding the bias unit

The most important aspect of model building in bankruptcy prediction lies in accuracy. As per the results in Table 6, training data predicted accurately is 93.8%, while testing is 92.2% accurate.

Table 7: Model Summary

Training	Cross-Entropy Error	372.757
	Percent Incorrect Predictions	6.2%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[s]
	Training Time	0:00:00.78
Testing	Cross-Entropy Error	181.972
	Percent Incorrect Predictions	7.8%

Dependent Variable: DEFAULT

Overall, the results of the function have an accuracy of 92.2%. Details are provided in Table 8. Training data has an overall accuracy rate of 93.8% and testing data has 92.2%.

Table 8: Classification

Sample	*Observed*	*Predicted*		
		NO	*YES*	*Percent Correct*
Training	NO	1908	50	97.4%
	YES	85	118	58.1%
	Overall Percent	92.2%	7.8%	93.8%
Testing	NO	839	30	96.5%
	YES	45	48	51.6%
	Overall Percent	91.9%	8.1%	92.2%

The visual outcome of an artificial neural network with one hidden layer structure is shown in Fig. 1.

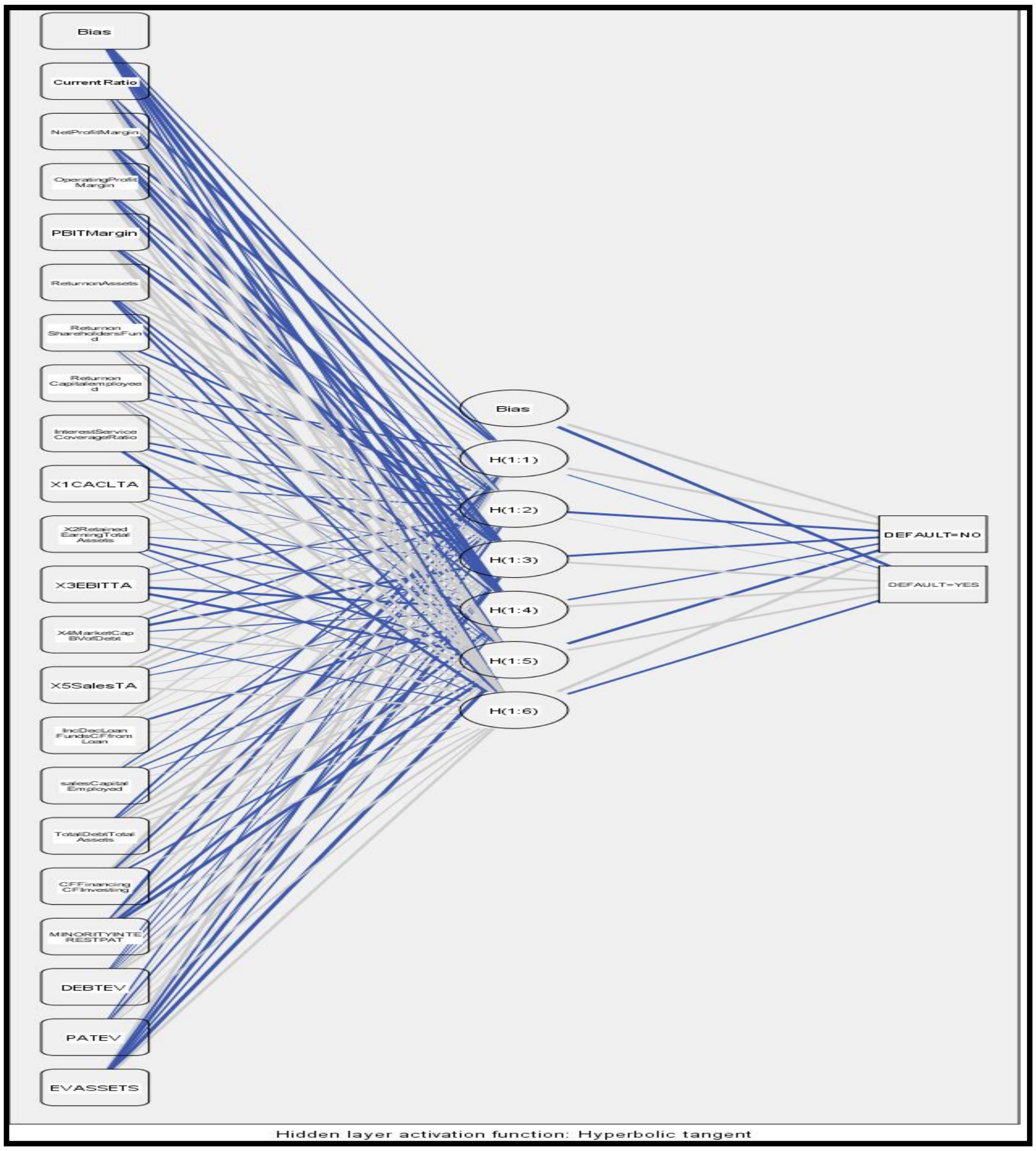

Fig. 1: Artificial Neural Network One Layer Structure

The function provides independent variable importance in Table 9. Highest is PBIT/Total Assets, followed by Enterprise Value/Total Assets, Operating Profit Margin, Cash Flow Financing/Cash Flow Investing, Total Debt/Total Asset, Sales/Capital Employed, Retained Earnings/Total Assets, Return on Shareholders' Funds, PBIT/Sales, and others.

Table 9: Independent Variable Importance

Ratios	*Importance*	*Normalised Importance*
PBIT/Total Assets	0.096	100.00%
EV/Total Assets	0.086	89.20%
Operating Profit Margin	0.065	67.70%
Cash-flow Financing/Cash-flow Investing	0.063	65.50%
Total Debt/Total Assets	0.06	62.30%
Sales/Capital Employed	0.058	60.10%
Retained Earnings/Total Assets	0.058	60.00%
Return on Shareholders' Funds	0.051	52.90%
PBIT Margin	0.049	51.40%
Net Working Capital/Total Assets	0.045	46.40%
Increase (Decrease) Loan Funds/Cash-flow from Loan	0.044	46.30%
Return on Assets	0.043	45.00%
Net Profit Margin	0.04	41.90%
Minority Interest/PAT	0.037	38.90%
Sales/Total Assets	0.035	36.70%
Debt/EV	0.032	33.70%
Return on Capital Employed	0.031	32.00%
PAT/EV	0.029	30.10%
Current Ratio	0.027	28.50%
Interest Service Coverage Ratio	0.025	26.20%
Market Capitalisation/BV of Total Debt	0.025	26.20%

Conclusion

This is a modest attempt to study the given data and find that with the use of artificial neural network, commercial banks in India can predict if the loan account will become a wilful default or not, with 92.2% accuracy. It provides meaningful insight on variables to be considered before disbursing and for monitoring purposes. Utmost importance should be given to PBIT/Total Asset ratio. Bankers should consider the insights seriously in case of a downward trend or major negative fluctuation in this ratio. Bankers can thereafter investigate the loan account and take action as per the guidelines of the central bank. Other variables to be equally considered include variables of importance: Enterprise Value/Total Assets, Operating Profit Margin, Cash Flow Financing/Cash Flow Investing, Total Debt/Total Asset, Sales/Capital Employed, Retained Earnings/Total Assets, Return on Shareholders' Funds, PBIT/Sales, and others.

The amount of NPA and NPA to Advance ratio are dreadful for public sector banks. The study indicates that public sector banks should give more emphasis on predicting the default using ANN instead of going for a cumbersome process of filing a post-default lawsuit. Artificial Intelligence has been used by banks across the globe and public sector banks should invest in this direction.

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