Bankruptcy Prediction of Manufacturing Companies of India Post-IBC : A Comparative Study Between Various Predictive Techniques

Simrat Kaur [1]
Adarsh Arora [2]
Anil Kumar Goyal [3]
Anjali Munde [4]

Abstract

Purpose : The primary goal was to forecast insolvency by comparing different bankruptcy prediction methods among Indian industrial enterprises.

Methodology : This study assessed the use of machine learning models in the financial industry. A comparison of random forests (RFs), decision trees (DTs), artificial neural networks (ANNs), and logistic regression was done. The consideration period for companies that were declared bankrupt under the 2016 Insolvency and Bankruptcy Code was April 1, 2017, until March 31, 2020. Data from 48 companies, 24 of which were bankrupt and 24 of which were not, was gathered two years ago.

Findings : In the comparative examination, the RF predictive technique outperformed the other predictive strategies in terms of accuracy.

Practical Implications : A company's financial characteristics provide valuable insights into its overall financial well-being. Examining a field of information that would be fascinating to regulators and investors will be facilitated by this study.

Originality : There has been little research on bankrupt companies after the IBC 2016 took effect. This study concentrated on predicting a company's bankruptcy following the implementation of the 2016 Insolvency and Bankruptcy Code.

Keywords : random forest, decision tree, artificial neural networks, logistic regression, bankruptcy

JEL Classification Codes : C45, C53, G33

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The manufacturing industry is still growing worldwide. It currently makes up 14% of employment and 16% of the global GDP. India is acknowledged as the second most prominent manufacturing nation globally. Through the implementation of numerous initiatives and policies, the Indian government hopes that

[1] *Research Scholar,* Amity University Noida, Noida - 201 313, Uttar Pradesh. (Email : simrat.kaur4@student.amity.edu)
ORCID iD : https://orcid.org/0000-0001-9359-2401
[2] *Professor,* Amity University Noida, Noida - 201 313, Uttar Pradesh. (Email : aarora@amity.edu)
ORCID iD : https://orcid.org/0000-0002-1358-7272
[3] *Associate Professor,* Maharaja Agrasen Institute of Management Studies, Rohini, New Delhi - 110 086.
(Email : dranilgoyal20@gmail.com) ; ORCID iD : https://orcid.org/0000-0003-2867-0084
[4] *Assistant Professor,* Southampton Malaysia Business School, University of Southampton, Malaysia.
(Email : anjalidhiman2006@gmail.com) ; ORCID iD : https://orcid.org/0000-0001-6809-1373

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manufacturing will contribute 25% of economic output by 2025 (Manral, 2022). One trillion US dollars might be generated by India's manufacturing sector by 2025. A staggering number of people are going bankrupt in the manufacturing sector, which is the second greatest contributor to the GDP (John, 2020). A total of 261 textile and leather companies and 266 basic metals companies had declared bankruptcy. The list of defaulters included more than 200 makers of food, beverage, and tobacco products, in addition to 154 chemical businesses (John, 2020).

Bankruptcy Board in India

On January 8, 1986, the Sick Industrial Companies Act (SICA) was approved by the president for the procedure of restructuring or winding up and has been in use ever since. The swift identification of sick or potentially sick businesses that possessed industrial operations, as well as their prompt recuperation or dissolution when necessary, was the main objective of the SICA. Due to the overlap between the SICA and Companies Act 2013 rules, the SICA was eliminated on December 1, 2016 (PwC, 2016).

The Insolvency and Bankruptcy Code (IBC), 2016, was enacted in 2016 to establish a new legal framework for time-bound insolvency and bankruptcy procedures for corporations, limited liability partnerships, partnership firms, and individuals (Insolvency and Bankruptcy Board of India, 2022). The IBC 2016, which established the groundwork for a market-driven and time-bound insolvency resolution framework, is regarded as one of the most significant historical transformations being carried about in the nation's economy. The stakeholders came to appreciate the Code's contents and selected the settlement process as it was intended. The Code produced significant benefits for both creditors and debtors because one of its main objectives is to balance the interests of all parties involved (Insolvency and Bankruptcy Board of India, 2022).

Financial Distress and Bankruptcy

One of the most captivating business headlines is a series of events pertaining to the financial crisis that involves the activities of public corporations. A financial crisis is thought to be the lowest point in terms of demand lowering, profitability drops, unemployment rises, and inflation rises. According to Jain and Bothra (2016), every economic sector fights for survival. Numerous bankruptcies harm the economy, causing a recession or depression. When businesses or individuals are in financial distress (FD), they are unable to meet their financial obligations and hence cannot produce profits. A legal action conducted by the business to relieve itself from debt obligations is filing for bankruptcy ("What is Bankruptcy? Definition of bankruptcy, bankruptcy meaning," 2022). Viswanatha Reddy (2012) asserted that larger clients can revoke orders and that a company's market value plummets dramatically when it faces financial challenges. A financially troubled business might have to postpone making payments on its debts until it declares bankruptcy or is liquidated.

Bankruptcy Prediction

Since it will assist the company's stakeholders in keeping an eye on the business's performance, the topic of bankruptcy prediction is essential. Bankruptcy is strongly predicted by financial difficulty, and early identification of it can help stakeholders respond quickly to address the situation. A financially distressed company may certainly incur costs without necessarily becoming bankrupt in the end (Farooq et al., 2018). The ability to predict organizations' financial difficulties with increasing accuracy is becoming increasingly important in the fields of accounting, finance, statistics, and other business disciplines (Yu et al., 2014). Halteh et al. (2018) described financial distress prediction (FDP) as the process of building statistical models that anticipate the financial collapse or performance of a company using information that is readily available to the public, such as financial metrics from accounting statements. FDP entails foreseeing an organization's financial challenges before they develop. It goes under a variety of titles, such as "credit default," "corporate failure," "financial insolvency," and "financial risk," to mention a few (Halteh et al., 2018). Restoration is more difficult as the financial difficulties are severe. In the latter stages of financial hardship, a company thus has a reduced probability of regaining its health (Farooq et al., 2018).

The main goal of this paper is to recommend a model for the early detection of bankruptcy in the Indian manufacturing sector. The results of this study are anticipated to benefit the Indian manufacturing sector. One of the research gaps is that, as a result of the implementation of IBC 2016, there has been relatively little research on bankruptcy data post-IBC 2016. This study uses post-IBC 2016 data to forecast bankruptcy. Owing to the absence of research on early warning system modeling for the Indian manufacturing sector following the adoption of IBC 2016, this study would contribute to the body of knowledge.

Another research gap is that there is nearly little study on bankruptcy prediction using machine learning methods in India. There is a high increase in the application of machine learning models in research due to their accuracy, therefore, this study contributes to the limited research on the prediction of bankruptcy using machine learning models, specifically in India. The significance and implementation of machine learning in current times are shown in this paper. This study demonstrates how machine learning can be applied to bankruptcy prediction to show how machine learning has developed for the benefit of society. First, this study builds bankruptcy models utilizing a variety of methods, including artificial neural networks (ANNs), logistic regression, decision trees (DT), and random forests (RFs). It compares how effectively they perform with bankruptcy data of India. The suggested study intends to investigate whether or not there is a substantial difference in the classification accuracy of all four models—logistic regression, DT, ANN, and RF. In order to keep a business from going bankrupt, this can help analyze and forecast its financial status.

The identified gaps in the field determine the research objectives that follow. The primary goals of this investigation are:

- ***R1 :*** To identify the financial variables of bankruptcy prediction.
- ***R2 :*** To study the impact of financial variables on the bankruptcy prediction of manufacturing companies in India.
- ***R3 :*** To conduct a comparative study across Indian manufacturing organizations using different machine learning techniques.

The information was gathered after IBC 2016. Financial information from businesses that are not bankrupt, as well as those that are, are taken into account. This study finds that DT-based strategies, such as RF, provide good accuracy outcomes with high AUC values following the application of machine learning algorithms.

Literature Review

Background

Beaver (1966) introduced the idea that financial ratios could be useful in models for predicting individual firm failure, financial crisis, and bankruptcy. This was the beginning of the prediction of bankruptcy. The first model to predict bankruptcy was developed by Altman (1968). Five variables were used to create the Altman *Z*-score. According to Altman, the model's short-term accuracy was 95%, but when it is for two or more years before the bankruptcy, that figure lowers to 72%. Altman *Z*-score is used in numerous research papers. Chandra and Awasthi

(2019) examined the insolvency risk of India's biggest commercial banks using the Altman *Z*- score. The Altman *Z*-score was employed by Ahuja and Singhal (2014) to assess the financial stability of Indian textile industry companies. Chitta et al. (2019) used it to check the financial soundness of top PSUs.

Distress measurement was used by Saji (2018) to compare stock market failures. *Z*-score offers compelling proof that, especially in a struggling industry, the company financials have a significant impact on the cross-sectional distribution of equity returns. The suggested *Z*-score identified 93% of manufacturing sector defaulting businesses a year prior to filing for bankruptcy (Shilpa Shetty & Vincent, 2021).

Using logit and probit models, Ohlson and Zmijewski examined the risk of bankruptcy, respectively (Ohlson, 1980; Zmijewski, 1984). A comparison of Altman and Ohlson's models was done by Chatterjee (2018), where both models were highly accurate at predicting the financial well-being and financial distress of widely held large-size corporations in India. Still, there was little difference in their prediction accuracies. The Zmijewski model and the Altman *Z*-score, which are based on credit risk models, were also evaluated in the study by Gupta and Gupta (2023) to evaluate the performance of the business following purchase and forecast bankruptcy, respectively.

Financial Ratios

The fact that the forecast was made using data from financial statements of corporations may be evidence of the informational value of those reports. Financial ratios have mostly been used to evaluate financial performance since they are capable of projecting financial distress and collapse (Binti et al., 2010). Tian et al. (2015) investigated the significance of financial ratios in forecasting the future risk of default of firms, and these ratios were discovered to be better indicators of financial distress among enterprises. Based on prior empirical research and their analytical judgment, Singh and Mishra (2016) chose 25 financial ratios to assess a company's leverage, liquidity, profitability, and turnover. Leverage, liquidity, profitability, and turnover are the main financial ratios that are found to be predictive of corporate failure in the majority of studies on the international or Indian markets. A study by Lin et al. (2011) found that liquidity plays a crucial role in predicting a financial collapse and that the debt ratio is relevant. Rather, one of the most significant markers of a company's financial difficulty is its liquidity. The value of asset and debt management ratios as a predictive analytical tool for corporate bankruptcy was demonstrated in the study by Ramesh and Senthil Kumar (2018).

Financial ratios and multiple discriminant analyses were employed in a paper by Bhunia and Sarkar (2011) to predict financial distress in Indian companies. Their research, nevertheless, was limited to a few pharmaceutical companies in the private sector. Mondal and Roy (2013), in their paper, developed a prediction model for steel companies and found that the rate of growth of earnings after tax and the debt-equity ratio are important predictors of sick steel firms. Debt ratio, working capital ratio, net income to total assets ratio, and total asset turnover ratio were all significant financial ratios. In contrast, the base lending rate was a significant macroeconomic variable in the paper by Alifiah (2014). By including financial ratios as inputs into models for predicting financial distress, the paper by Halteh et al. (2018) showed a large concentration on the financial aspect.

Machine Learning

Comparing machine learning techniques like support vector machines (SVM) and RF against statistical techniques like logistic regression, it was found that the machine learning techniques achieve 10% greater accuracy (Barboza et al., 2017). The main focus of the study conducted by Kim et al. (2020) was to evaluate machine learning techniques for forecasting company bankruptcy systematically.

According to the literature review, the unbalanced nature of the data causes the prediction performance to worsen if missing values are not addressed from the start (Mahapatra et al., 2020). For prediction using machine learning techniques, it is important that pre-processing is done properly. The pre-processing techniques have a substantial impact on the predictions made by the bankruptcy data set. During the pre-processing stage, missing values need to be initially filled using the mean of the corresponding feature vector before using the synthesis data generation technique to resolve the unbalanced (Mahapatra et al., 2020). Smith and Alvarez (2022) looked at creative and unique models for forecasting bankruptcy using a machine learning technique in order to classify and separate bankrupt enterprises from non-bankrupt companies more precisely.

Artificial Neural Networks

Numerous methods have been used to predict firm insolvency and financial crises, including artificial intelligence and statistical methods; many studies have discovered that artificial intelligence surpasses traditional statistical methods (Jerez et al., 2010). According to Hertz et al. (1991), algorithm-based computer systems called ANNs can be developed to replicate the inner functioning of the human brain. The first time NNs were used to approach a bankruptcy prediction problem was in the paper by Odom and Sharda (1990). ANNs, such as the one applied by Coats and Fant (1993), were a non-parametric method that has been adapted for FDP. Altman et al. (1994), among others, have conducted another research adopting NNs. The “black-box” NN systems drawbacks were specially highlighted, such as the indicators' illogical weightings and the training stage's overfitting, both of which have a negative impact on forecast accuracy. To predict bankruptcy, Hosaka (2019) used a convolutional neural network on the observed financial ratios data.

Decision Trees and Random Forests

Logistic regression is used in many corporate FDP research. Much research uses DTs for FDP, Chen (2011) being one of them. DT models gradually divide a data set into smaller sections by building a series of tree-based classification rules (Halteh et al., 2018). The benefits of high fault tolerance, universal applicability, and parallel processing are seen as the features of artificial neural networks. It is being found that DTs do not need a lot of training; thus, the models they produce are simple to comprehend and can handle missing values and prevent data overfitting using tree pruning (Chi & Shen, 2022).

Breiman (2001) described similar techniques, like RFs, but they have the advantage of classifying data using multiple DTs. Creamer and Freund (2004) were the first researchers to use RFs for the issue of bankruptcy prediction. According to the study by Chandra et al. (2009), it was found that there is only a small number of research that has examined business FDP adopting RF. The focus of current research is mostly on the use of firm-specific variables for failure predictions, with accounting modeling techniques using data from financial statements—standing out as the most important of these (Agrawal & Maheshwari, 2019).

Research Methodology

Data Descriptions

Regarding Indian bankruptcy data, there are few reliable databases. The National Company Law Tribunal (NCLT), established under the provisions of the Companies Act of 2013, serves as the refereeing authority for insolvency and liquidation matters of corporate entities by the Insolvency and Bankruptcy Code of 2016 (Hafeez & Kar, 2021). The method used to collect the data is secondary. Information was gathered between April 1, 2017, and March 31, 2020. The Insolvency and Bankruptcy Board of India (IBBI) website provides a source of information on insolvent firms, with 77 listed entities having been declared bankrupt. The manufacturing sector employed 49 of the 77 enterprises. It was discovered during data collection that 14 companies' financial records for prior years were missing, making their data unavailable. Out of the remaining 35 companies, only 24 companies have data from two years prior to bankruptcy. Twenty-four non-bankrupt companies were selected based on the bankrupt company's sector and the total number of assets of bankrupt companies (Lakshan & Wijekoon, 2012). For this investigation, information was gathered from 48 different businesses. The PROWESS software is used to gather data from the previous two years for both bankrupt and non-bankrupt companies.

The number of insolvent businesses from the manufacturing industry is shown in Table 1. A total of 24 companies consist of 14 sectors of the manufacturing industry. Out of 24, two are from the cable sector, four are from the textile sector, two are from the steel sector, and two are from the mining sector. Each company is from the auto ancillaries sector, the automobile sector, the chemical sector, and the paper sector. Three come from the petroleum and gas industry. One each from the non-ferrous metal, electronics, and FMCG industries. The latter two businesses are in the agro-processing industry.

Variables

Beaver (1966) proposed several ratios for anticipating bankruptcy, essentially dividing them into the categories of profitability, liquidity, and leverage. Similar ratios were selected in research by Altman (1968). We selected 15 financial ratios to measure a firm's leverage, liquidity, profitability, and turnover based on previous empirical literature. Table 2 represents the dependent and independent variables identified for this study.

Table 1. ***Sector-Wise Bankrupt Manufacturing Companies***

Sector	Number of Companies
Cable Sector	2
Textile Sector	4
Metal Ferrous (Steel) Sector	2
Mining Sector	2
Auto Ancillaries	2
Automobile Sector	1
Chemical Sector	1
Paper Sector	1
Gas and Petroleum Sector	3
FMCG Sector	1
Electronics Sector	1
Non-Ferrous Metal Sector	1
Glass Sector	1
Agro Processing Sector	2

Table 2. ***Variables***

Variables	
Dependent Variable: Bankrupt or Non-Bankrupt	Bankrupt companies declared by NCLT from 2017 to 2020. Two-year prior data is taken. Non-bankrupt companies based on the same sector and the total number of assets were selected from 2017 to 2020, and two-years prior data was taken.

Independent Variables		
Working capital to total assets	Working capital/ Total assets	(Altman, 1968; Ohlson, 1980; Nandi et al., 2019)
Retained earnings to total assets	Retained earnings/ Total assets	(Altman, 1968; Shilpa Shetty & Vincent, 2021)
Earnings before interest and tax (EBIT) to total assets	EBIT/ Total assets	(Altman, 1968; Springate, 1978)
Sales to total assets	Sales/ Total assets	(Altman, 1968; Springate, 1978)
Earnings before tax (EBT) to current liabilities	EBT/ Current liabilities	(Springate, 1978)
Debt to asset ratio	Total debt/ Total assets	(Ohlson, 1980; Zmijewski, 1984)
Current ratio	Current assets/ Current Liabilities	(Zmijewski, 1984)
Return on assets (ROA)	Net income/ Total assets	(Ohlson, 1980; Zmijewski, 1984)
Quick ratio	(Current assets-inventory-prepaid expense)/ Current liabilities	(Chen et al., 2006; Mselmi et al., 2017)
Cash flow ratio	Cash flow from operations/ Total debt	(Cao et al., 2011; Ong et al., 2011)
Interest coverage ratio	EBITDA/ Interest expense	(Hu & Ansell, 2007; Xiao et al., 2012)
Return on equity (ROE)	Net income/ Shareholders' equity	(Chen, 2011; Fallahpour et al., 2017)
Earnings per share (EPS)	(Net income- preferred dividend)/Average outstanding shares of the company	(Chen, 2011; Kim, 2018)
Debt to equity ratio	Total debt/ Shareholders' equity	(Hu & Ansell, 2007; Mselmi et al., 2017)
Cash ratio	(Cash and cash equivalent + short-term investments)/ Current liabilities	(Chen et al., 2006; Fallahpour et al., 2017; Hu & Ansell, 2007).

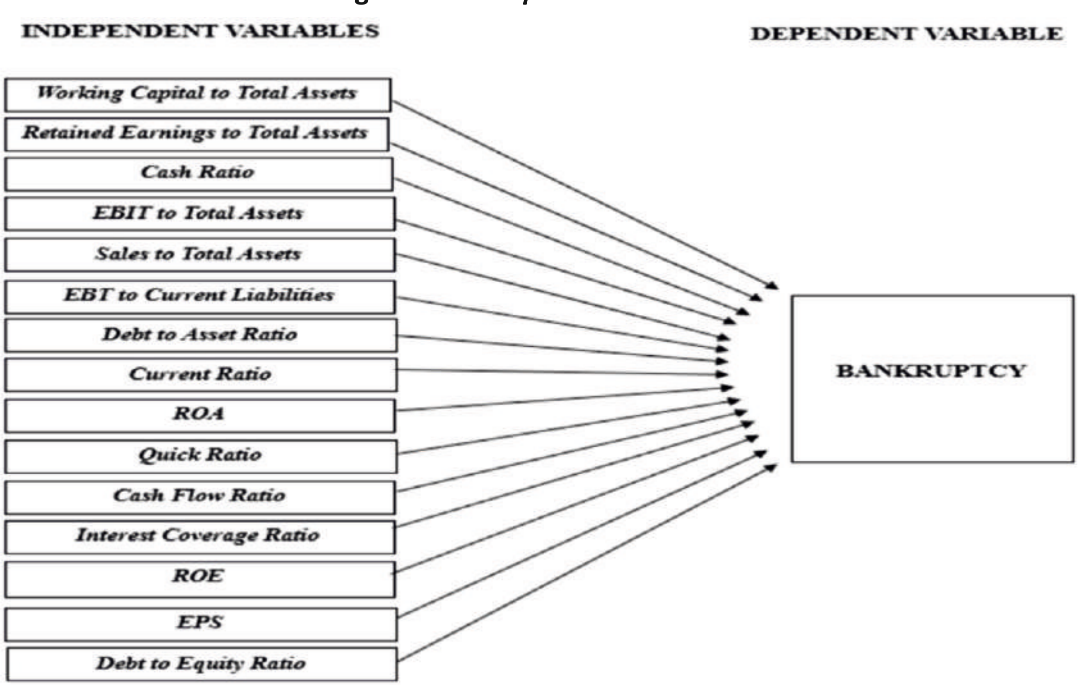
Based on the research objectives, the hypotheses are developed for objective two following the selection of financial factors for the study.

- **H01a :** There is no significant impact of working capital on total assets on bankruptcy.
- **Ha1a :** There is a significant impact of working capital on total assets on bankruptcy.
- **H01b :** There is no significant impact of retained earnings on total assets on bankruptcy.
- **Ha1b :** There is a significant impact of retained earnings on total assets on bankruptcy.
- **H01c :** There is no significant impact of EBIT on total assets on bankruptcy.
- **Ha1c :** There is a significant impact of EBIT on total assets on bankruptcy.
- **H01d :** There is no significant impact of sales to total assets on bankruptcy.
- **Ha1d :** There is a significant impact of sales to total assets on bankruptcy.
- **H01e :** There is no significant impact of EBT on current liabilities on bankruptcy.
- **Ha1e :** There is a significant impact of EBT on current liabilities on bankruptcy.
- **H01f :** There is no significant impact of the debt-to-asset ratio on bankruptcy.
- **Ha1f :** There is a significant impact of the debt-to-asset ratio on bankruptcy.
- **H01g :** There is no significant impact of the current ratio on bankruptcy.
- **Ha1g :** There is a significant impact of the current ratio on bankruptcy.

- **H01h :** There is no significant impact of return on assets on bankruptcy.
- **Ha1h :** There is a significant impact of return on assets on bankruptcy.
- **H01i :** There is no significant impact of quick ratio on bankruptcy.
- **Ha1i :** There is a significant impact of quick ratio on bankruptcy.
- **H01j :** There is no significant impact of the cash flow ratio on bankruptcy.
- **Ha1j :** There is a significant impact of the cash flow ratio on bankruptcy.
- **H01k :** There is no significant impact of interest coverage ratio on bankruptcy.
- **Ha1k :** There is a significant impact of interest coverage ratio on bankruptcy.
- **H01l :** There is no significant impact of return on equity on bankruptcy.
- **Ha1l :** There is a significant impact of return on equity on bankruptcy.
- **H01m :** There is no significant impact of earnings per share on bankruptcy.
- **Ha1m :** There is a significant impact of earnings per share on bankruptcy.
- **H01n :** There is no significant impact of the debt-to-equity ratio on bankruptcy.
- **Ha1n :** There is a significant impact of the debt-to-equity ratio on bankruptcy.
- **H01o :** There is no significant impact of cash ratio on bankruptcy.
- **Ha1o :** There is a significant impact of cash ratio on bankruptcy.

Based on these hypotheses, a conceptual framework is framed in Figure 1.

Figure 1. ***Conceptual Framework***



Python software was used to import and sanitize the data as it was being gathered. Missing values were examined when the data was imported into Python. It was discovered that the dataset contained a total of nine missing values. Missing values were filled using the sum average. After sorting missing data, duplication in the data was checked. It was found that there is no duplication in the data. After that, outliers were removed. Boxplot was created to check whether there are outliers or not.

Predictive Techniques

The type of research of this study is analytical. Logistic regression, RF, ANNs, and DT predictive models are selected for comparison in this research. Based on previous studies, it is found that DT-based models are showing high accuracy in predicting bankruptcy as compared to traditional models like logistic regression. Through this study, we will check whether DT models are better than other models or not. Bankruptcy prediction is performed using supervised learning in Python.

Analysis and Results

Binary logistic regression with a *p*-value of 0.05 is used to evaluate the impact of all the identified financial variables on the bankruptcy of the companies.

Table 3 shows that seven variables do not significantly affect bankruptcy, supporting the null hypothesis. Those variables are sales to total assets, EBT to current liabilities, ROA, cash flow ratio, ROE, EPS, and debt-to-equity. Working capital to total assets, retained earnings to total assets, EBIT to total assets, debt-to-asset ratio, current ratio, quick ratio, interest coverage ratio, and cash ratio are the variables that have a significant impact on bankruptcy, i.e., the null hypotheses are rejected for these variables. The logistic regression equation, which predicts the dependent variable based on the independent variable, has coefficients called the *B* values. There is an inverse relationship between the dependent and independent variables if it is negative.

Table 3. ***Hypotheses Results***

Variables	*B*	Sig.	Decision
Working capital to total assets	–3.512	**0.008**	**H01a is rejected.**
Retained earnings to total assets	–1.331	**0.007**	**H01b is rejected.**
EBIT to total assets	–53.493	**0.007**	**H01c is rejected.**
Sales to total assets	–0.003	0.983	H01d is accepted.
EBT to current liabilities	–196.766	0.181	H01e is accepted.
Debt to asset ratio	4.784	**0.002**	**H01f is rejected.**
Current ratio	–2.881	**0.001**	**H01g is rejected.**
ROA	–9123.017	0.494	H01h is accepted.
Quick ratio	–2.927	**0.001**	**H01i is rejected.**
Cash flow ratio	0.61	0.530	H01j is accepted.
Interest coverage ratio	–2.039	**0.017**	**H01k is rejected.**
ROE	–0.015	0.789	H01l is accepted.
EPS	–73.590	0.889	H01m is accepted.
Debt to equity ratio	0.012	0.531	H01n is accepted.
Cash ratio	–43.152	**0.004**	**H01o is rejected.**

Table 4. ***Category of Selected Variables***

Variables	Category
Working capital to total assets	Liquidity Ratio
EBIT to total assets	Profitability Ratio
Retained earnings to total assets	Profitability Ratio
Current ratio	Liquidity Ratio
Quick ratio	Liquidity Ratio
Interest coverage ratio	Leverage Ratio
Cash ratio	Liquidity Ratio
Debt-to-asset ratio	Leverage Ratio

- There is a negative relationship between working capital to total assets and bankruptcy.
- There is a negative relationship between retained earnings to total assets and bankruptcy.
- There is a negative relationship between EBIT to total assets and bankruptcy.
- There is a negative relationship between the current ratio and bankruptcy.
- There is a negative relationship between quick ratio and bankruptcy.
- There is a negative relationship between interest coverage ratio and bankruptcy.
- There is a negative relationship between cash ratio and bankruptcy.
- The debt-to-asset ratio shows a positive relationship with bankruptcy.

According to Table 4, the majority of the variables that demonstrated the impact come from the areas of leverage, liquidity, or profitability.

One of the key ratios to evaluate a company's creditworthiness is liquidity. Argenti concluded in his research that one of the main factors contributing to a firm's insolvency was its high amount of debt (Argenti, 1976). According to the paper by Beaver (1966), companies with less liquid assets are more likely to file for bankruptcy. Profitability ratios estimate a company's performance. The ratio demonstrates how efficiently the company uses its resources and manages its spending to generate sufficient profits for its shareholders. This study suggests that unprofitable businesses are more likely to go bankrupt. The turnover ratio, or the ratio of sales to total assets, has no bearing on bankruptcy. Eight factors listed above are taken into consideration for additional comparison analysis in the bankruptcy forecast.

After checking the impact of the identified variables, a hypothesis for objective three is formulated.

- **H02 :** There is no significant difference between all four predictive models.
- **Ha2 :** There is a significant difference between all four predictive models.

For analysis, the data was divided into training and testing periods for all four models in Python. A total of 70% data was trained, and 30% data was tested for prediction. The random state was set at 42 (Luo et al., 2016). Scaling of the data was done using StandardScaler. The accuracy and area under the curve (AUC) value of each prediction model has been evaluated after application to train-test the data set. A comparison of accuracy and AUC of the selected predictive techniques, i.e., logistic regression, ANN, DT, and RF, is done in this paper.

The outcomes of the different prediction methods are :

Table 5. ***Predictive Techniques***

Predictive Techniques	Accuracy	AUC
Logistic Regression	73.33%	0.89
Artificial Neural Networks	87.88%	0.91
Decision Tree	93.33%	0.92
Random Forest	93.75%	0.98

Table 5 represents the results received after applying machine learning techniques to Python. The accuracy and AUC value of all four models are mentioned. As we can see from the results, the accuracy and AUC values of all four models vary; therefore, we reject H02. The RF technique outperformed all the other predictive techniques with the highest accuracy of 93.75%. The DT shows the second-highest accuracy of 93.33% in predicting bankruptcy. ANN shows an accuracy of 87.88%, and last, logistic regression shows the least accuracy of 73.33% for bankruptcy prediction.

The AUC value for each of the four models is shown in Figures 2, 3, 4, and 5. The *y*-axis indicates true-positive

Figure 2. ***Logistic Regression***

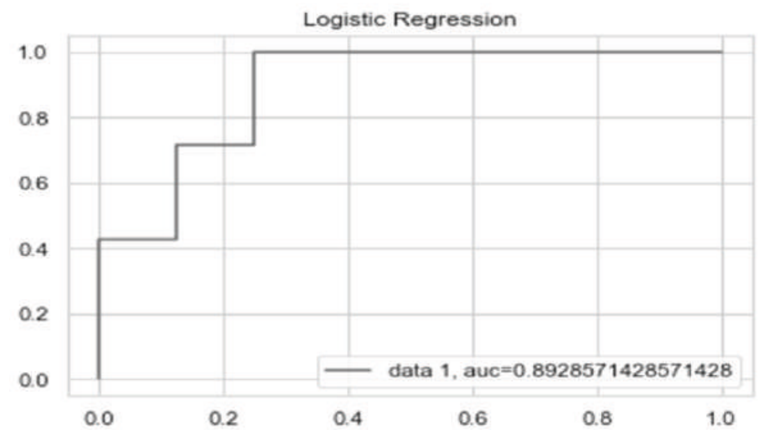


Figure 3. ***Artificial Neural Networks***

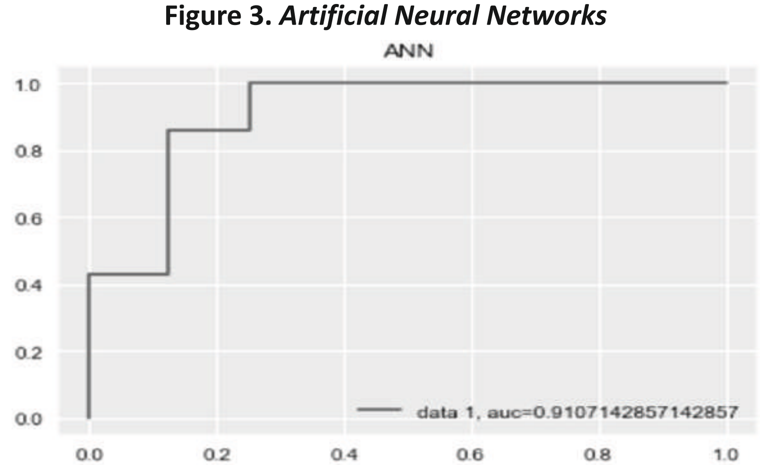


Figure 4. *Decision Tree*

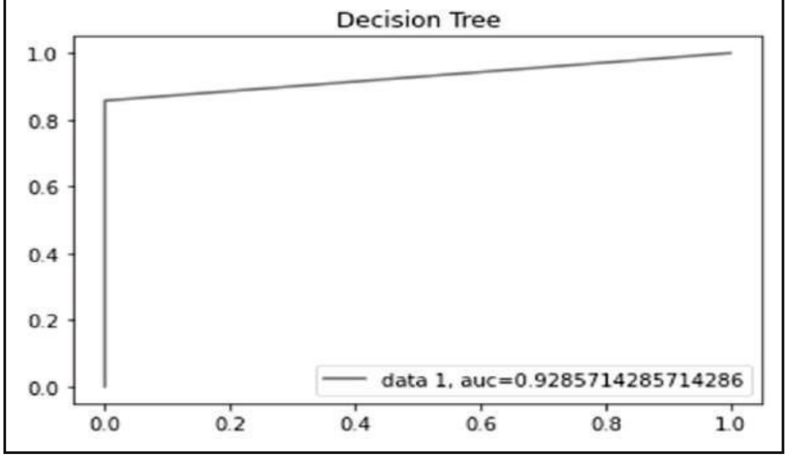
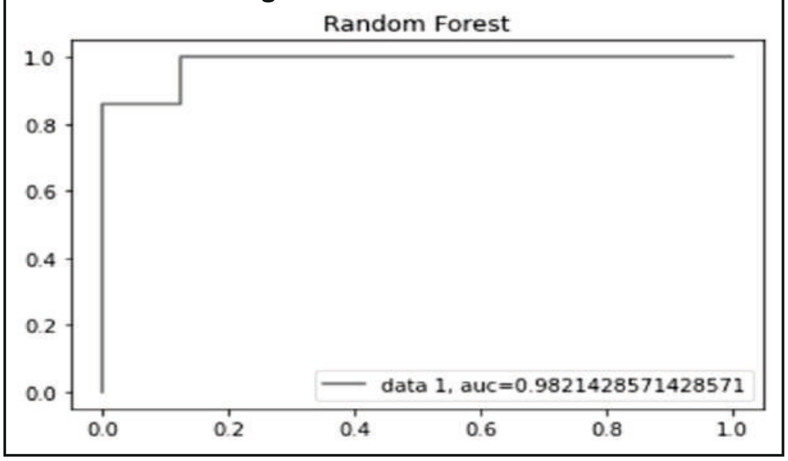


Figure 5. *Random Forest*



rates, while the x-axis represents false-positive rates. The area under the curve, or AUC value, is regarded as good if it is more than 0.7. As can be seen from the figures, all four models have an AUC value of more than 0.7, but the RF shows the highest AUC value at 0.98 then the DT at 0.92. The DT and ANN AUC values are nearly identical, with the ANN displaying an AUC value of 0.91. The lowest AUC value is displayed by logistic regression, at 0.89.

Theoretical and Managerial Implications

One of the most vital and growing topics in finance is bankruptcy prediction. The prediction approaches used must be accurate. Financial ratios of previous well-established models have been taken. Ratios from Altman (1968), Ohlson (1980), Zmijewski (1984), and Springate (1978) are considered along with a few new variables from previous literature. In this study, it is witnessed that not all the ratios that were considered in previously established models show a significant impact on bankruptcy. The sales to total asset ratio was not significant in this study, while it was in earlier Altman (1968) and Springate (1978) models. This study provides fresh insights for future research and contributes to the body of prior research on bankruptcy prediction.

DT models show more accuracy than other bankruptcy models as was seen in previous studies too. Due to the accuracy of predictive approaches, the companies will be able to adhere to an early warning of bankruptcy. This study makes an effort to examine a field of information that investors and governing bodies both find interesting. Investors will be able to decide whether or not to invest in a company if a way of anticipating bankruptcy is developed. Because it will be able to monitor business debtors and bankruptcies across the nation and take necessary further action, the government will also profit from bankruptcy prediction.

Conclusion

According to this study, the ratios of working capital to total assets, retained earnings to total assets, quick ratio, debt to asset ratio, current ratio, EBIT to total assets, interest coverage ratio, and cash ratio can all be used to predict bankruptcy in the manufacturing sector of India as they showed significant impact on the prediction of bankruptcy. In contrast, ratios like EBT to current liabilities, ROA, cash flow ratio, ROE, EPS, and debt-to-equity show no impact on the prediction of bankruptcy. Turnover ratios like sales to total assets do not show any impact in this research, which is being vastly used in previous research and established models of Altman (1968) and Springate (1978).

It is found that there is a difference between the accuracy of all four models. RF shows the highest results in predicting bankruptcy as compared to ANN, DT, and logistic regression, with 93.75%. It is demonstrated that RF is superior to other predictive techniques. There is a slight difference between the accuracy of the DT and the RF, as the DT shows an accuracy of 93.33%. In previous studies like Olson et al. (2012), a DT is considered superior to ANN. It is also witnessed that DT-based techniques are showing higher accuracy than models highly used for the prediction of bankruptcy, like ANN, logistic regression, and MDA. In this study, logistic regression shows the lowest accuracy of 73.33%. The least accurate method has been demonstrated to be logistic regression, a finding consistent with earlier research such as Chen's (2011) paper. The AUC value is good for all four models because it is more than 0.7. RF displays the greatest score at 0.98, while logistic regression displays the lowest value at 0.89.

Limitations of the Study and Scope for Future Research

It is being witnessed that there is a limitation in India on data availability as data is not that much and easily available after the implication of IBC 2016. The data of this paper is limited; therefore, for future studies, researchers can predict bankruptcy on bigger data and in a bigger timeframe. Future research on the prediction of bankruptcy in other Indian industries is a suggestion that this study intends to recommend. This study is restricted in terms of the number of input variables. As more categories of variables can be taken into consideration for the study, this research can be expanded by including more variables. When predicting bankruptcy in India, independent variables to be considered are macroeconomic conditions and business governance indicators. Future research endeavors may choose to use other variables in their analysis to forecast bankruptcy rates in India.

Authors' Contribution

Simrat Kaur was a big contributor to the manuscript's composition and gathered the bankruptcy data from the IBBI website. Dr. Adarsh Arora examined the literature. Dr. Anil Kumar Goyal gathered the PROWESS data on non-bankruptcy. The data was evaluated and examined by Dr. Anjali Munde.

Conflict of Interest

The authors verify that they have no relevant financial or non-financial interests to disclose. There are no competing interests to be disclosed.

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About the Authors

Simrat Kaur is pursuing a Ph.D. in the prediction of bankruptcy using machine learning techniques among manufacturing companies from Amity University, Noida, Uttar Pradesh. Her interest is in the area of machine learning, predictive models, financial distress prediction, and data analytics.

Dr. Adarsh Arora is a Professor at Amity University, Noida, Uttar Pradesh. He has more than 18 years of experience and has published 11 papers in peer-reviewed journals. He also has experience in financial accounting, cost accounting, corporate accounting, management accounting, income tax, and corporate tax planning.

Dr. Anil Kumar Goyal is working as an Associate Professor at Maharaja Agrasen Institute of Management Studies, GGSIP University, Delhi. He has more than 18 years of academic experience. He has more than 50 research papers published in journals, including Scopus and ABDC-listed journals.

Dr. Anjali Munde is presently working with Southampton Malaysia Business School, University of Southampton, Malaysia. She has published 15 research papers in reputed journals, which are indexed in Scopus, IEEE, and Web of Science. Her areas of research interest include data science, business analytics, and machine learning.