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# Predicting of default of Indian Manufacturing sector: A comparative study of Logit, MDA and PROBIT models

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**Abstract**
Financial risk is the most crucial risk for a corporate and various models develop to predict the financial health of corporates. Various financial variables play a crucial role in differentiation firms between solvent and in-solvent among then total assets is the one which is critical in identifying the financial status of the firm. The present study focus on three basic model for default prediction such as MDA, Logit and PROBIT for default prediction of selected Indian manufacturing sectors (160 Non-default and 91 default firms) for a period form 1 April,2005-31 March,2022. Among these three models Logit perform better with 84% accuracy while PROBIT and MDA shows only 51 % and 28 % accuracy respectively and significant variables are WC/TA, RE/TA, TBD/TA, Total Liability/ Total Assets, Revenue/TA.

**Keywords**: MDA, Logit, PROBIT, Financial variables, Total assets.

**Introduction**
Bankruptcy prediction was undoubtedly an area of research of special interest, primarily because firms and economies were keen to avoid costly spill overs from corporate defaults. Financial crunch problem of a firm is directly associated with the firm's leverage decision. When the companies fail to service the debts & other financial obligations than they are said to have defaulted. And when these firms have to undergo a legal process of either liquidation of assets or winding up, it is said to be the situation of bankruptcy. SEBI disclosed 75000 crores amount as of Dec 31, 2019 as a defaulted amount of 60 listed firms (Economic times, 2021).

The Altman Z-score was a sensational innovation in its application of MDA for the classification of companies as either solvent or at risk of default based on financial ratios. Several models have been developed in the intervening years, in an attempt to refine or extend the Z-score. Aims of the forecasting studies are not only to predict default event rather it also manages to recognise the various key predictors and time of default. Green (1978) and Gibson (1982) advocated liquidity, leverage, activity and profitability ratios as the major predictors of firm's financial performance Similarly, Chen & Shimerda (1981) inspect the utility of financial ratios in forecasting or predicting bankruptcy prediction. Bandyopadhyay developed an extension of the traditional Z-score models by adding logistic regression as well as non-financial variables such as the market conditions and management quality. The hybrid model shows increased predictability in particular, the case of Indian bond market that surpasses the base Z-score. Among others which include non-financial variables in bankruptcy model is Ohlson's Y-score model of 1980. Far superior newer versions outweigh older methodologies such as Altman's MDA model and Ohlson's O-score model.

Although the models MDA and logistic regression remain valid for one-period predictions, structural models have gained attention because of their dynamic approach-for calculating a firm's asset value against its liabilities to evaluate its potential for bankruptcy. Structural models can be called as the "distance to default" associated with annual growth in the assets and on other side liabilities volatility of the firm. There are various prediction methods and models that can be used by Indian corporate to practice internal risk management and predict potential defaults. The majorly used methods is consisting of either statistical methods or firm's specific structural models along with machine and artificial intelligence based models that are being used to assess firm's creditworthiness.

The present study is grouped into 4 portions. Firstly, comprises Introduction and literature review of the study. Section second comprise of Rationale and objectives related with study. The section third exhibits the empirical results and findings and analytical part of the study. The lastly composed the conclusion pert alone with discussion of the empirical findings and results of in the study.

**Review of Literature**

Bankruptcy prediction is one of the real concerns in research, mainly with the desire of companies and economies to avoid the costly consequences of corporate failures. The work done by Altman; applying MDA for classification of companies into defaulting and non-defaulting on the basis of financial ratios; opened doors for the development of many models aiming at improving or extending the Z-score over time. While structural models are now applied, models like MDA and logistic regression are still very good at predicting a single period. Structural models measure a firm's asset value relative to its liabilities and have gained popularity in recent times for their dynamic nature of bankruptcy prediction. Structural models measure "distance to default" using annual growth rate of liabilities and volatility of liabilities of a firm. Quite a number of articles have utilized the Altman Z-score to predict bankruptcy within different industries and markets.

The study chooses a sample data of 66 listed manufacturing firms for default prediction with financial ratios. Here in the study a sample pair of 25 firms consider in group I and in group II 14 diversified assets firms consider. Among the financial ratios the profitability ratios contribute the most in prediction of default such as Sales/TA ratio. The study conclude with 95% classification accuracy with Error Type II is 3 % considerate. In forward projection of default study acquire 72% accuracy in 2 year time horizon category (Altman, 1968).

Begley et al. (1996) re-considered that how preciseness the Ohlson & Altman Z-score traditional model alone with accuracy .Here, it is observed that the Ohlson model perform superior than the Altman's model. (Beglery, Ming, & Watts, 1996).

Altman & Sabato (2005) studied the appropriateness of the Z-score on SMEs in the United States. They were successful in making the Z-score applicable even on SMEs and found out that firm size specific models have to be used because SMEs come with a different set of characteristics. Other authors have applied the Z-score on steel and oil drilling industries which point out that the Z-score is a very useful tool when defaulting is concerned (Altman & Sabato, 2005).

Bandyopadhyay (2006) suggested a hybrid model, which combines MDA with logistic regression for the setting of an Indian market. The model produced 91% level of classification accuracy and also exhibited a high predictive power, outperforming the basic Z-score (Bandyopadhyay A. , 2006).

Wang and Campbell(2010) cling to the appropriacy of Z-score model in default prediction of Chinese firms (Wang & Campbell, 2010).Hence the Altman Z-score models robustness & simplicity support (Lifschutz & Jacobi, 2010). Bhunia and Sarkar (2011) employ MDA for Indian firms and conclude that ratios related specifically with profit and liquidity of a firm are more significant in prediction distress (Bhunia & Sarkar, 2011).

The study assessed the financial statement of 122 listed manufacturing firms from 1999 to 2007 using logit and MDA. The study conclude that the models are competent to predict default 1-year prior with profitability, financial structure, liquidity ratios. Further, the ratios of Net profit to TA is found most significant and prominent predictor for both the models. However, the MDA & logit model found 84% accuracy for 1st year and 80% accuracy for 2nd year (Vuran et al., 2009).

Pal (2013) employ discriminant analysis on a sample set of Indian steel companies for a period of 20 years from1991-2012 and found that profitability and efficiency ratios like ROI, debtor and fixed asset turnover ratios are important indicators in classification steel firms into financial healthy and financial weak companies (Pal S. , 2013).

The default prediction of 47 Indian selected firms during a time horizon of 2007-2013 utilizing option based model and suggest that default probability negatively related with distance to default and positive related with asset volatility (Sharma, Kumar, & Upadhyay, 2014).

Bosnia banking market firms default predicted by Memic,2015, Here these firms grouped into Default and non-default to forecast the default through Logit and MDA tools and spotted Return on Asset ratio is more appropriate for locating default prediction (Memic, 2015).

Default prediction models was developed through MDA and Logit methods of analysis for the sample set of 75 (solvent and non-solvent each) Moroccan firms during 2011-2013.Here, Logit perform much better with 82% accuracy rate then MDA having only 71%. The effective predictors identified in the study are sales/WC, NI/Assets, Debt/Asset, Stock/Sales, Asset/CL. (El-Ansari & Benabdellah, 2017).

Madhushani and Kawshala (2018) evaluate the ramification of financial constrains over the financial viability of 29 Sri Lanka firms. Conclude that Altman Z-score model come up with a positive relation to ROE and ROA on the other hand leverage positively related with ROE and negatively related with ROA (Madhushani & Kawshala, 2018).

The study is empirical & make a comparison between five default prediction models i.e Ohlson, Altman, Grover, Zmijewski and Springate & finding shows that Springate and Zmijewski models are more precise in advance prediction of probability of default (Agarwal & Patni, 2019).

Nandi et. al. (2019) measured the credit risk of 12 Indian Oil drilling firms employ MDA. the sample data is collected for 5 years, 2012 to 2017. The study calculated Z-score by financial ratios. The MDA classify the firms to various zones according to the reported Z score. Study advocated the contribution of WC/TA in the credit risk assessment is most. (Nandi et al., 2019).

MDA and Logit analysis models compared along with their variables sensitivity & industry beta. A sample of various industries sectors composed of 135 firms studied and found logit models having more significant than MDA in both in-sample and validation data with Logit accuracy lies 81.7 % (In-sample) and 65.7% (validation data) (Agrawal & Maheshwari, 2019)
More studies also report the success of the algorithms. Madan et al. (2020) published the case study of the decision tree versus the random forest models: its prediction power rated at 73-80% (Madan, Kumar, Keshri, Jain, & Nagrath, 2020).

**Rational of the study**
After having an extensive review of literature it has been found that various statistical and financial models used in prediction of default of firms like Altman (1968), Beaver (1966), Smarander (2014), Memic (2015), EI-Ansari & Benabdellah (2017), Agrawal and Maheshwari (2019). But there are limited studies which focus Indian manufacture sectors and only the financial ratios used in these studies whereas market and economic variables used in less number of studies. This study uses a sample of selected Indian manufacture firm over a long horizon for identify the financial status and key predictors of default in selected Indian firms with the help of three models such as MDA, Logit and PROBIT model and try to identify which model's prediction efficiency is better for Indian Manufacturing sector.
**Objective of the current Study**
- To develop the model for default of selected Indian manufacturing sectors using MDA, Logit, PROBIT
- To compare the developed models to identify the best model for selected Indian manufacture sector.
- To locate the major predictors of default amongst the selected Indian manufacture sector.

**Method and Data**
The study employ three popular models for prediction of default such as: MDA, Logit and PROBIT.
**MDA (Multivariate discriminant analysis)**
It is a statistical tool basically used to ordered the observations into predefined groups built on multiple predictor variables. MDA differentiate between group (non-default and default) entities through creating a linear combination of predictor. MDA is applicable where the data is of linear & equal covariance across groups.
Discriminant function:
"$Z= \beta0+ \beta1X1+ \beta2X2+ \beta3X3 \ldots\ldots\ldots\ldots +\beta kXk$
If Z>Zc(Critical value),it is classified into non-default group otherwise default group."

**Logit Model**
It is a type of regression analysis where dependent variable is of binary nature. It models the probability of default as a function of Independent variables, using logistic function to ensure that the probability lie in between 0 and 1. Logit model handle the non-linear relationships between the probability of default and Independent variables.
Logit model formula

"$$P(Y=1) = \frac{1}{1+e^{-(\beta0+ \beta1X1+ \beta2X2+ \beta3X3 \ldots\ldots\ldots\ldots +\beta kXk)}}$$"

**PROBIT Model**
This models estimate the default probability but assuming a cumulative normal distribution, for error term, this is similar to Logit model, but where the error term is assumed to follow a normal distribution then PROBIT is preferred. Logit & PROBIT both are more flexible in handling non-linear relationship.
PROBIT Model Function
"$P(Y=1|X)= \Phi(\beta0+ \beta1X1+ \beta2X2+ \beta3X3 \ldots\ldots\ldots\ldots +\beta kXk)$"
This model transforms the linear combination of predictors (independent variables) into probability using cumulative distribution function.

**Sample Data and Period of Study**
This study utilizes the sample set of 17 years' time interval from 1st April 2005 to 31st March 2022 for prediction the default probability & develop the credit risk models. The sample cases encompass data of Indian BSE listed manufacture firms. The sample observations are applied to develop the model. The sample data comprise with various Indian manufacture sector such as: Agriculture and farm, Automobile, Construction and Engineering, Furniture, Metal, Oil and Gas Drilling, Packaged food, Paper, Shipping and Electronics these sector are the major contributory sectors in manufacturing and the study composed with sample data

**Table 1: Default and Non-Default manufacturing firms**

| **Particulars** | **Number of Firms** |
|---|---|
| **Default** | 91 |
| **Non-default** | 160 |
| **Total** | 251 |

**Source: Sample data classification in excel.**

**Sources of Data**

Accounting information or financial data gathered directly from the financial statements of selected firm, from BSE website the share price information was retrieved. Along with this, the economic data from the World bank database. The default status of the firms confirmed from the audited report of firms of 17 years from 1st April 2005 to 31st March 2022.

**Description of the sample Data**

Case Summaries present in two sorts of cases whereas sample data utilize for development of default prediction with MDA, LOGIT AND PROBIT model and processed on IBM SPSS version 23 and utilize to developed models.

**Variables used in the study**

1) **Independent variables**: In the study there are 33 independent variables use such as WC/TA, RE/TA, GRTA, Sales Growth, OCF/TD, EBIT/TA, MVE/TBD, Sales/TA, CA/CL, NI/TA, NP/TE, TBD/TA, Log(TA/GDP), EBIT/Interest, OCFR, OCF/TI, Inventory Turnover (IT), Fixed Assets Turnover (FAT), D/E, MVE/BE, TOTAL LIABILITIES(TL)/ TOTAL ASSETS(TA), Sales Growth/GNP Growth, ROA, REVENUE/TA, ROE, NI/REVENUE, (CA-INVENTORY)/CL, EPS/MVE, OCF/CL MP/EPS, MP/BV, X and Y

1) **Dependent variable**

Z categorized into default as 1 and non-default as 0.

**Default Prediction Functions Utilize in the Study**

Based on the early studies finding, the present study selected MDA, LOGIT AND PROBIT to predict the default of selected Indian manufacturing firms and compared these model to find the suitable models for selected Indian manufacture firms. The LOGIT performed effectively in the past studies for predicting solvent and in-solvent firms.

**Table 2: Model developed using Logit, MDA and PROBIT:**

| **Models** | **Developed models** |
|---|---|
| **Logit** | L=1.744-1.171*WC/TA-2.071*RE/TA-0.004*MVE/TBD-0.744*CA/CL+0.620*TBD/TA+0.001*EBIT/Interest-2.808*GRTA-0.010*Inventortturnover+0.045*D/E-1.045*TOTALLIABILITY/TOTALASSETS+0.017*ROE+0.813*(CA-INVENTOTY)/CL-0.702*REVENUE/TA-0.001*MVE/BE-0.221*EPS/MVE-1.616*X |
| **MDA** | Z=-1.945+0.849*WC/TA+1.732*RE/TA-0.391*EBIT/TA+5.873*NI/TA-0.690*TBD/TA+1.033*GRTA+0.640*TOTALLIABILITY/TOTALASSETS-6.309*ROA+0.462*REVENUE/TA+0.527*EPS/MVE |
| **PROBIT** | Z=0.444-0.349*WC/TA-2.116*RE/TA-1.319*EBIT/TA-0.002*MVE/TBD-1.047*SALES/TA-0.312*CA/CL+0.380*TBD/TA-0.005*Inventoryturnover-0.538*TOTALLIABILITY/TOTALASSET-0.064*LogTA/GDP +0.009*ROE+0.325*(CA-INVENTORY)/CL-0.466*REVENUE/TA |

**Source: Based on results on sample data run in SPSS.**

Common variable which contributes in all three developed models are WC/TA, RE/TA, TBD/TA, Total Liability/ Total Assets, Revenue/TA.

**FINDINGS**

**LOGIT Statistical test results**

Table 3: Cox & Snell R square values and Hosmer and Lemeshow test values and also elucidate the 2 log likelihood value comes out to be 1568.488 which indicates overall fit of logistic regression model and Cox 7 Snell R Square value come out to be 0.276 represent that 27.6% variation is accounted for by the model which is quite satisfactory and Nagelkerke R Square value i.e. 0.487 which demonstrate that 48.7 % of variance in the dependent variable, here moderately strong relationship represented by this value.

**Table 3: Cox & Snell R square and Hosmer and Lemeshow test**

| Step | -2 Log likelihood(Value) | Cox & Snell R Square(Value) | Nagelkerke R Square(Value) | Hosmer and Lemeshow test Chi-square(Value) | Sig. |
|---|---|---|---|---|---|
| 1 | 1568.488a | .276 | .487 | 29.153 | .000 |

**Source: Based on results on sample data run in SPSS.**

**MDA statistical test results**

Table 4: R, Eigen value, Wilk's Lambda, Chi-Square demonstrate that the Eigenvalue is 0.334 reflect moderate explanatory power of the model. Wilk's Lambda value is 0.750 explain that there is moderate group difference this value close to zero suggest better discrimination. The Chi-Square value is 874.149 and sig (p=0.000) indicates that this function significantly discriminates between groups. Here, R (0.403) & R Square (0.163) and Adjusted R Square (0.155) explain moderate relationship. The high F-test value i.e. 21.369 and sig(p=0.000) indicates the model as statistically significant. But R-Square suggest improvement in model fit.

**Table 4: R, Eigen value, Wilk's Lambda, chi-square.**

| Model | R(Value) | R Square (value) | Adjusted R Square(Value) | Std. Error of the Estimate | Eigenvalue | Wilks' Lambda (Value) | Chi-square | Sig. |
|---|---|---|---|---|---|---|---|---|
| 1 | .403[a] | .163 | .155 | .335 | .334[a] | .750 | 874.149 | .000 |

**Source: Based on results on sample data run in SPSS.**

**Comparative analysis of Developed models (PROBIT, MDA and Logit results)**

Insignificant variables found for PROBIT analysis with the help of factor analysis found EBIT/Interest, GRTA, MP/BV, MVE/BE and EPS/MVE. The number of significant variables found in developed models are illustrated below in Table 5: Variables (Significant).

**Table 5: Variables (Significant)**

| **Particulars** | **PROBIT** | **MDA** | **Logit** |
|---|---|---|---|
| **Significant variables** | 13 | 10 | 16 |

**Source: Based on results on sample data run in SPSS.**

Here, the significant variables are extracted on Sample data run in SPSS version 23, while the independent variables which contributes in development of the model in case of PROBIT are found 13 and for MDA it is 10 and in Logit there are more variables found significant and contribute in model development for default prediction are 16. The materiality of the variables is depending on the significant values of the variables found in the result of sample data run on SPSS, while in case of MDA structure matrix values >0.3 value, for Logit its variable in equation value significant value of independent variable found >0.5, and for PROBIT its parameter estimators value >0.5.

**Success rate of developed models**

Table 6: calculated prediction with developed models represent the classification accuracy or success rate of each developed models along with error Type II and I. These values elucidate the percentage of accuracy associated with each developed models along with misclassification problem in the form of Error Type II.

**Table 6: Calculated prediction with developed models**

| Particulars | PROBIT | MDA | Logit |
|---|---|---|---|
| **Accuracy** | 51.13% | 28% | 84% |
| **Error Type I** | 0.02035330261 | 0.8413978495 | 0.1366602687 |
| **Error Type II** | 0.7494407159 | 0.02460850112 | 0.3177777778 |

**Source: Based on results on sample data run in SPSS.**

Here PROBIT show 51.13% accuracy which is higher than MDA but lower than Logit, but Error Type II is very higher i.e. 74.94%. MDA provide 28% accuracy which shows MDA efficiency is very low in prediction of default but Error Type II is only 2.46% which is better than Logit model. Here the logit provide 84% accuracy and Error Type I is 13.66% and Error Type II is 31.77% which is quite high. The classification accuracy and robust models found here is Logit as the accuracy % is quite effective with a moderate misclassification od data problem. But if ranked these developed models then MDA placed lower form all and don't shows pleasant result for selected manufacturing sectors while accuracy is very low i.e. 28%.

## CONCLUSION

In the present study while compare the developed models there are certain common variable found such as WC/TA, RE/TA, TBD/TA, TOTALLIABILITY/TOTALASSETS this shows that total assets of a firm play a critical role in identifying the financial status. The developed Logit model show higher accuracy i.e. 84% while the MDA developed model and PROBIT developed model accuracy are 28% and 51% respectively. In respect of Indian manufacture sector (160 non-default and 91 default firms), the MDA and PROBIT model shows week prediction efficiency as compare to Logit model but Error Type II in case of MDA developed model is more significant which is quite low i.e. 0.0246 as compared with PROBIT and Logit Error Type II are 0.749 and 0.31 respectively. The major contributor from independent variables are WC/TA, RE/TA, TBD/TA, Total Liability/ Total Assets, Revenue/TA as all these predictors belongs to financial variables categories, so its suggested that the financial or accountable variables are very effective in identify a financial distress situation, the role of Total Assets is prime in all, along with these financial indicators some marketing and economic variables also contribute in default prediction such as EPS/MVE and LOG (TA/GDP) suggested that while amalgamation of marketing and economic variables with financial variables then prediction capacity increased and advocated by many previous studies such as (Sharma, Kumar, & Upadhyay, 2014), (Vuran et al., 2009), (Aguado & Benito, 2012).However, for such a long horizon of 17 years the Logit or Logistic regression shows significant result while compare with PROBIT and MDA models.

## REFERENCES

1. Agrawal, K., & Maheshwari, Y. (2019). Efficacy of industry factors for corporate default prediction. *IIMB Management Review, 31*(1), 71–77. https://doi.org/10.1016/j.iimb.2018.08.007
2. Ali, M., & Abbas, A. (2015). Companies bankruptcy prediction by using Altman models and comparing them. *Research Journal of Finance and Accounting, 6*(14), 154.
3. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy.*The Journal of Finance, 23*(4), 589–609.
4. Altman, E., & Sabato, G. (2005). Modeling credit risk for SMEs: Evidence from the US market. *Abacus, 43*(3), 332–357 https://doi.org/10.2139/ssrn.872336
5. Arnis, N., Karamanis, K., & Kolias, G. (2019). Detecting creative accounting in businesses in financial distress. *Accounting and Finance Research, 8*(2), 232–244.
6. Bandyopadhyay, A. (2006). Predicting probability of default of Indian corporate bonds: Logistic and Z-score model approaches. *Journal of Risk Finance, 7*(3), 255–272. https://doi.org/10.1108/15265940610664942
7. Bandyopadhyay, A. (2020). Prediction probability of default of Indian corporate bonds: Logistic and Z-score model approaches. *Journal of Financial Risk Management, 12*(2), 255–273.
8. Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*(1966), 71–111.
9. Beglery, J., Ming, J., & Watts, S. (1996). Bankruptcy classification errors in the 1980s: An empirical analysis of Altman's and Ohlson's models. *Review of Accounting Studies, 1*(4), 267–284.
10. Bhunia, A., & Sarkar, R. (2011). A study of financial distress based on MDA model: A case study of Indian pharmaceutical companies. *Research Journal of Finance and Accounting, 2*(1), 81–94.
11. Chen, K., & Shimerda, T. A. (1981). An empirical analysis of useful financial ratios. *Financial Management, 10*(1), 51–60.

12. Cimpoeru, M. (2015). An analysis of financial ratios and their role in predicting bankruptcy. *Journal of Financial Studies, 8*(2), 45–59.
13. Cybinski, P. J. (2001). The predictive accuracy of bankruptcy prediction models: A case study of Australian companies. *Australian Journal of Management, 26*(2), 107–130. https://doi.org/10.1177/031289620102600201
14. El-Ansari, F., & Benabdellah, P. M. (2017). Prediction of bankruptcy: Evidence from Moroccan agricultural companies. *The International Journal of Business & Management, 3*(6), 176–185.
15. Ganelasingam, K., & Kumar, R. (2001). The effectiveness of financial ratios in predicting corporate failure: An Australian study. *Accounting Research Journal, 14*(1), 35–50.
16. Gibson, C. H. (1982). Financial statement analysis: A theoretical and practical approach. *The Accounting Review, 57*(3), 556–570.
17. Green, R. (1978). Predicting corporate bankruptcy: A comparative analysis of financial ratios. *Journal of Business Finance & Accounting, 5*(3), 295–302. https://doi.org/10.1111/j.1468-5957.1978.tb00210.x
18. Hassan, E. ul, Zainuddin, Z., & Nordin, S. (2017). A review of financial distress prediction models: Logistic regression and multivariate discriminant analysis. *Indian-Pacific Journal of Accounting and Finance, 1*(3), 13–23. https://doi.org/10.52962/ipjaf.2017.1.3.15
19. Hus, C. (2017). Applying Z-score models in aviation finance education: A case study of some US carriers. *International Journal of Education and Social Science, 4*(3), 9–14.
20. Islam, F., & Nabi, A. (2015). Impact of probability to default on sugar sector using firm level variables. *Journal of Economic Info (JEI)*, 1–5.
21. Jayadev, M. (2006). Predictive power of financial risk factors: An empirical analysis of default companies. *Vikalpa, 31*(3), 45–56. https://doi.org/10.1177/0256090920060304
22. Liang, Q. (2003). Corporate financial distress diagnosis in China: Empirical analysis using credit scoring models. *Hitotsubashi Journal of Commerce and Management, 38*(1), 13–28.
23. Lifschutz, S., & Jacobi, A. (2010). Prediction bankruptcy: Evidence from Israel. *International Journal of Business and Management, 5*(4), 133–141.
24. Madan, M., Kumar, A., Keshri, C., Jain, R., & Nagrath, P. (2020). Loan default prediction using decision tree & random forest: A comparative study. *ICCRDA, IOP Conference Series. Materials Science and Engineering, 1022,* 012042.
25. Madhushani, I. H., & Kawshala, B. (2018). The impact of financial distress on financial performance: Special reference to listed non-banking financial institutions in Sri Lanka. *International Journal of Scientific and Research Publications, 8*(2), 393–405.
26. Memic, D. (2015). Assessing credit default using logistic regression and multiple discriminant analysis: Empirical evidence from Bosnia and Herzegovina. *Interdisciplinary Description of Complex Systems, 13*(1), 128–153. https://doi.org/10.7906/indecs.13.1.13
27. Nandi, A., Sengupta, P. P., & Dutta, A. (2019). Diagnosing the financial distress in oil drilling and exploration sector of India through discriminant analysis. *Vision, 23*(4), 364–373. https://doi.org/10.1177/0972262919862920
28. Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*(1), 109–131.
29. Pal, S. (2013). A study on financial distress in Indian steel industry under globalization. *Journal of Business and Management*, 49–53.
30. Sharma, C., Kumar, R., & Upadhyay, R. (2014). Predicting probability of default. *Primax International Journal of Commerce and Management Research*, 5–13.
31. Smaranda, C. (2014). Scoring functions and bankruptcy prediction models – Case study for Romanian companies. *Procedia Economics and Finance, 10*(14), 217–226. https://doi.org/10.1016/s2212-5671(14)00296-2
32. Vuran, B., Kelimeler, A., Işletmelerde, :, Başarısızlık, F., Tahmini, B., Analizi, D., Analizi, L. R., & Sıkıntı, F. (2009). Prediction of business failure: A comparison of discriminant and logistic regression analyses. *İstanbul Universitesi İşletme Fakültesi Dergisi Istanbul University Journal of the School of Business Administration, 38*(1), 47–65.
33. Wang, Y., & Campbell, M. (2010). Do bankruptcy models really have predictive ability? Evidence using China publicly listed companies. *International Management Review, 6*(2), 77–82.