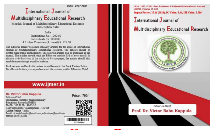
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FINANCIAL DISTRESS PREDICTION THROUGH AI TOOLS AND ALTMAN Z: A STUDY ON FINANCIAL LEVERAGE OF LISTED INDIAN MANUFACTURING FIRMS

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Abstract:

Financial distress forecasting has emerged as a key to the interaction between the financial stability and the capital structure of a firm. This project aims at predicting financial distress in listed Indian companies as a result of applying AI (Artificial Intelligence) techniques to predict using the financial leverage ratios. Leverage ratios are used to measure the distress level with the help of AI-based models. The paper examines the financial records of four Indian manufacturing companies in the span of four years and concludes that AI models are more predictive, as compared to the conventional Altman Z-score method. The findings suggest that financial distress and leverage ratios have a strong correlation, which means that AI-based tools can serve as a valuable early warning system to managers, investors, and regulatory authorities.

Keywords : Financial Distress, Altman Z, Random Forest, Logistic Regression, Linear Regression, ANN and XGBoost as well as financial leverage.

Introduction

Financial stress is a serious, quantifiable disorder that can be an indication of bankruptcy (Sachdev et al., 2022). It denotes the likelihood with which a company can go bankrupt and this is determined by the liquidity status and the availability of credit (Hendal et al., 1996). A firm is financially troubled when it constantly makes losses, breaks loan agreements, or fails to fulfill its financial commitments (Dakare et al., 2019). The 2020 data provided by the IBBI (Insolvency and Bankruptcy Board of India) shows that the number of CIRPs (Corporate Insolvency Resolution Processes) initiated has been growing, as 6, 036 in 2020 and 8,175 in 2024, which suggests the growing need to identify financial distress in a timely manner. The manufacturing industry of India is an important constituent of the economy as it contributes significantly to GDP and employment. The majority of manufacturing companies are very dependent on debt capital. Although fixed rates of interest, greater flexibility, and the possibility of tax benefits are some of the advantages of debt financing, the optimal debt level must be determined to ensure profitability and value of the firm (Radmehr et al., 2023). Nevertheless, leverage has been referred to as a two-sided sword because it can increase the earnings per share but on the other hand increase the financial risk. The cause of financial instability and increasing probability of financial distress can be achieved when the debt levels become excessively high (Li and Xiuxia, 2025).

Both financial distress among companies and pose major challenges to the stakeholders. Therefore, companies should anticipate financial distress as soon and accurately as they can to prevent bankruptcy.

The traditional models, including Altman Z, of predicting financial distress are numerous and are based on the ratio analysis or econometric models. Regardless of such improvement in data access, the development of Artificial Intelligence potentiated the possibilities to forecast financial distress ahead of time and correctly with the help of Machine Learning models. The current study examines how AI models, namely logistic regression, Random Forests, Linear Regression, Artificial Neural Networks, and XGBoost can be used to forecast the occurrence of financial distress in Indian Manufacturing companies.

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Review of Literature

Nair and Sachdev (2022) have created a country-specific financial distress prediction model on the Indian manufacturing firms with the logistic regression. Their research reviewed 574 firms in 34 manufacturing industries and used 18 financial ratios to form and substantiate the model, which proved to have a good predictive power. According to Sana Ramzan and Lokanan (2024), ANN model exhibited high predictive accuracy and reliability in detecting financial distress with an accuracy of 98%. Mishra and Tandon (2021) narrowed down their interest to predict financial distress among 75 Indian commercial banks through a linear discriminant analysis (LDA) model, logistic regression model, and ANN model depending on five years of data (2015-2019). They found that logistic as well as LDA models had similar predictive accuracy. Sehgal et al. (2021) in another study investigated the important microeconomic variables that contributed to financial distress in India and the predictive ability of binomial logit, ANN and SVM models. They found that *machine learning models* especially SVM and ANN performed better than traditional methods, and when used to make one year ahead forecasts. Moreover, Shrivastava et al. (2020) compared the Random Forest algorithm with Tree Net algorithm to predict bankruptcy in Indian companies and discovered that the Tree Net approach had a better classification and predictive accuracy.

Statement of the problem

In India, the companies that are referred according to IBC(Insolvency and Bankruptcy Code) have been on the rise every year. The capital-intensive industries including manufacturing are especially sensitive to financial crisis, and hence the threats to their sustainability and development are quite high. Early and accurate diagnosis of financial distress is thus of massive importance to the investors, creditors, policymakers and other stakeholders. Failure to predict financial instability in manufacturing companies may have dire economic implications, such as reduction in employment, downward investments and instability in the entire market. Despite the widespread use of the traditional methods such as the Altman Z-score in predicting distress, the methods are not often capable of making accurate and prompt predictions since they lack flexibility in dynamic financial markets and fail to uncover complex interaction between the leverage indicators. Conversely, AI-based algorithms like Random Forests, Logistic Regression, Linear regression, Artificial Neural Networks (ANNs), and XGBoost have the ability to operate complex and high-dimensional datasets which increase the accuracy and efficiency of predicting financial distress. The proposed research will provide a comparison of predictive accuracy of the Altman Z model and AI approaches in terms of accuracy and early detection with financial leverage variables to see whether AI-based models are more accurate and can detect possible issues earlier compared with traditional methods, therefore, leading to the creation of the effective early warning systems of the manufacturing industry in India.

Need for the study

The manufacturing industry is among the key sectors of the Indian economy and it plays a very important role in the growth of the GDP as well as in the employment sector. But more and more manufacturing firms are being part of the insolvent and are falling under Insolvency and Bankruptcy Code (IBC) to be sorted out under *'Corporate Insolvency Resolution Process (CIRP)'*. This has become a serious issue of concern. A large debt to equity ratio tends to make financial distress more severe in that it decreases the power of a company to settle the debt thus exposing it to insolvency and increasing the probability of bankruptcy. According to Andrade and Kaplan (1998), high leverage level increase default risk and reduce the ability to raise cash hence it is a major cause of financial instability. Timely detection of financial distress especially where leverage is very high will allow firms to take proactive steps and enhance their financial conditions. As the concept of Machine Learning (ML) and Artificial Intelligence (AI) emerges, new models of predicting financial distress have emerged, which are more accurate than the previous ones. However, such AI-based models have not been compared to conventional tools such as the Altman Z-score in the Indian manufacturing industry.

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Study's Objectives:

1. To examine the predictive accuracy of the Altman's Z-score and AI models on financial distress in listed manufacturing companies based on the financial leverage indicators.
2. To evaluate the relationship between the primary financial leverage ratios and likelihood of the financial distress among the manufacturing companies in India.
3. To identify the most powerful financial distress predictors by implementing AI-based predictions.

Research Hypothesis

H01: There is no difference in predictive accuracy in the financial distress identification of the Altman Z and AI-based models.

H 0 2: There is no correlation between Financial Leverage ratios and the probability of financial distress in the Indian manufacturing firms.

Design and Methodology

The research is based on a quantitative, comparative research design, which implies the use of empirical aspects to identify financial distress in companies based on the Altman Z-score system and AI-based predictive models including Logistic Regression, Random Forests, linear regression, XGBoost, and ANN(Artificial Neural Networks).

The research design will include model development, validation and performance comparison using the determination of accuracy of prediction. In order to ascertain the association in between the financial leverage ratios and the financial distress, linear regression analysis is performed at the 5% level of significance. The population will be all manufacturing companies listed in the NSE, and a sample of four companies, namely, Tata Steel, Hindustan Unilever Limited (HUL), Ashok Leyland, and JSW Steel will be used as the study sample. The study will be based on secondary data of the financial statements of the companies, annual reports involving the period 2022-2025.

The Altman Z-score model, is the model used in assessing the risk of bankruptcy because it uses ratios to assess profitability, leverage, liquidity and activity.

In the case of the implementation of AI models, *Interest Coverage Ratio, Debt-to-Equity Ratio, Total Debt-to-Total Assets, Current Ratio and EBIT-to-Total Assets*, as independent variables, and Financial Distress as the dependent binary variable (1, 0) are used.

Data Analysis and Interpretation

1.1 Table Showing Altman Z score of the Tata Steel. Co.

Year	1.2*(WC/TA)	1.4*(RE/TA)	3.3*(EBIT/TA)	0.6*(MVE/TL)	1.0*(Sales/TA)	Z Score
2025	-0.09812	0.60449	0.298107	0.918739	0.521447	2.24466
2024	-0.06779	0.494306	0.179362	1.081462	0.573973	2.261319
2023	-0.0641	0.514815	0.350254	0.774078	0.551802	2.126854
2022	-0.12095	0.482454	0.696949	0.099294	0.581213	1.738955

(Source: Annual reports of Tata Steels)

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1.2 Table Showing Altman Z score of the HUL. Co.

Year	1.2* (WC/TA)	1.4*(RE/TA)	3.3*(EBIT/TA)	0.6*(MVE/TL)	1.0*(Sales/TA)	Z Score
2025	0.080094	0.152705	0.61792	10.92052	0.784914	12.55616
2024	0.122887	0.188323	0.598424	12.22965	0.784537	13.92382
2023	0.07388	0.187609	0.605555	16.70739	0.823446	18.39788
2022	0.063719	0.163314	0.561743	13.76791	0.848803	15.40549

(Source: Annual reports of HUL)

1.3 Table Showing Altman Z score of the Ashok Layland. Co.

Year	1.2* (WC/TA)	1.4*(RE/TA)	3.3*(EBIT/TA)	0.6*(MVE/TL)	1.0*(Sales/TA)	Z Score
2025	0.041458	0.437411	0.590193	1.002059	1.518177	3.589298
2024	-0.02243	0.312177	0.564861	0.795895	1.624913	3.275414
2023	0.030264	0.302112	0.350498	0.675541	1.599891	2.958306
2022	-0.00543	0.261561	0.134494	0.620334	1.066614	2.077574

(Source: Annual reports of Ashok Layland)

1.4 Table Showing Altman Z score of the JSW Steel. Co.

Year	1.2* (WC/TA)	1.4*(RE/TA)	3.3*(EBIT/TA)	0.6*(MVE/TL)	1.0*(Sales/TA)	Z Score
2025	0.070844	1.585634	0.927751	1.38481	2.755524	6.724562
2024	-0.1771	1.574748	1.394463	1.101784	3.136864	7.030758
2023	-0.00133	0.332535	0.22894	0.865579	0.761897	2.187625
2022	0.009954	0.345938	0.578751	1.061938	0.729539	2.726121

(Source: Annual reports of JSW Steels)

1.5 Table Showing the Mean Altman Z score of Companies

Company Name	Tata Steel. Co.	HUL	Ashoka Layland	JSW steel
Average Z score	2.092947	15.07084	2.975148	4.667266
Zone	Grey	Safe	Grey	Safe
Distress Status	0	0	0	0

The table above indicates that Tata Steel is ranked 100 on the Altman Z score. Grey Zone includes Co and Ashok Layland. HUL and JSW Steel are placed in Green Zone, which means that they are highly solvent.

The AI models' applicability in the establishment of Financial Distress

In order to analyze the relationship between the likelihood of financial distress and capital structure ratios, five Artificial Intelligence (AI) models were used. In the study, the researchers employed the key financial variables, such as Debt-Equity Ratio, Interest Coverage Ratio, EBIT to Total Assets (EBIT/TA), Z-Score, and Current Ratio as predicting variables of the chosen firms. The following table shows the impact of these ratios on the probability of companies experiencing financial distress. To train a model and do model evaluation, a 5-fold stratified K-fold cross-validation was used to promote sound,

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unbiased performance evaluation. In this, the dataset was divided in five segments and the training-testing cycle was repeated five times such that each segment served as test set once. To create consistent and reproducible results, a constant value of the random state, 42 was kept. (Source - Trae Code editor).

1.6 Table showing Financial Distress Prediction: Using Logistic Regression Model

Company Name	2022	2023	2024	2025
Tata Steels	0	0	0	0
HUL	0	0	0	0
Ashoka Layland	1	1	1	1
JSW Steels	1	1	1	1

Predicted Financial Distress: Healthy =0, Distress = 1 (Values Predicted using TRAE Software)

1.7 Table Showing Financial Distress Prediction: Using Random Forest Model

Company Name	2022	2023	2024	2025
Tata Steels	0	0	0	0
HUL	0	0	0	0
Ashoka Layland	1	1	1	1
JSW Steels	1	1	1	1

Predicted Financial Distress: Healthy =0, Distress = 1 (Values Predicted using TRAE Software)

1.8 Table showing Financial Distress Prediction: Using Linear Regression Model

Company Name	2022	2023	2024	2025
Tata Steels	0	0	0	0
HUL	0	0	0	0
Ashoka Layland	1	1	1	1
JSW Steels	1	1	1	1

Predicted Financial Distress: Healthy =0, Distress = 1 (Values Predicted using TRAE Software)

1.9 Table showing Financial Distress Prediction: Using XGBoost

Company Name	2022	2023	2024	2025
Tata Steels	0	0	0	0

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HUL	0	0	0	0
Ashoka Layland	1	1	1	1
JSW Steels	1	1	1	1

Predicted Financial Distress: Healthy =0, Distress = 1 (Values Predicted using TRAE Software)

2.0 Table showing Financial Distress Prediction: Using Artificial Neural Networks

Company Name	2022	2023	2024	2025
Tata Steels	1	1	1	1
HUL	1	1	1	1
Ashoka Layland	1	1	1	1
JSW Steels	1	1	1	1

Predicted Financial Distress: Healthy =0, Distress = 1 (Values Predicted using TRAE Software)

The above AI models except the Artificial Neural Networks model indicated the same results because Tata steel Co. and HUL Co. are financially healthy, and Ashoka leyland and JSW steel are financially distressed in all the four years, whereas the Artificial Neural Networks model concluded that each of the four companies are financially distressed.

Comparison of the Predictive performance of the Altman Z model with the AI models

2.1 Table showing Comparative Performance of Random Altman Z and AI models

Model	Accuracy	Mean Precision (class 1)	Mean Recall (class1)	Mean F1-Score	AUC-ROC	Timeliness	Strengths
Altman Z score	50%	0.50	1.00	0.6666	1.00	Moderate	Simplicity, Industry-tested
Logistic Regression	94%	1.00	0.88	0.9285	1.00	High	Statistical Interpretability
Random Forest	100%	1.00	1.00	1.0000	1.00	Very High	Handles Nonlinear relationships
Linear Regression	100%	1.00	1.00	1.0000	1.00	High	Suitable for Simple data having a linear relationship
XGBoost	94%	0.90	1.00	0.9444	0.94	High	Performs well on small data sets and is more interpretable
Artificial Neural Networks	88%	1.00	0.75	0.8571	1.00	High	Enables learning of highly complex patterns in unstructured data

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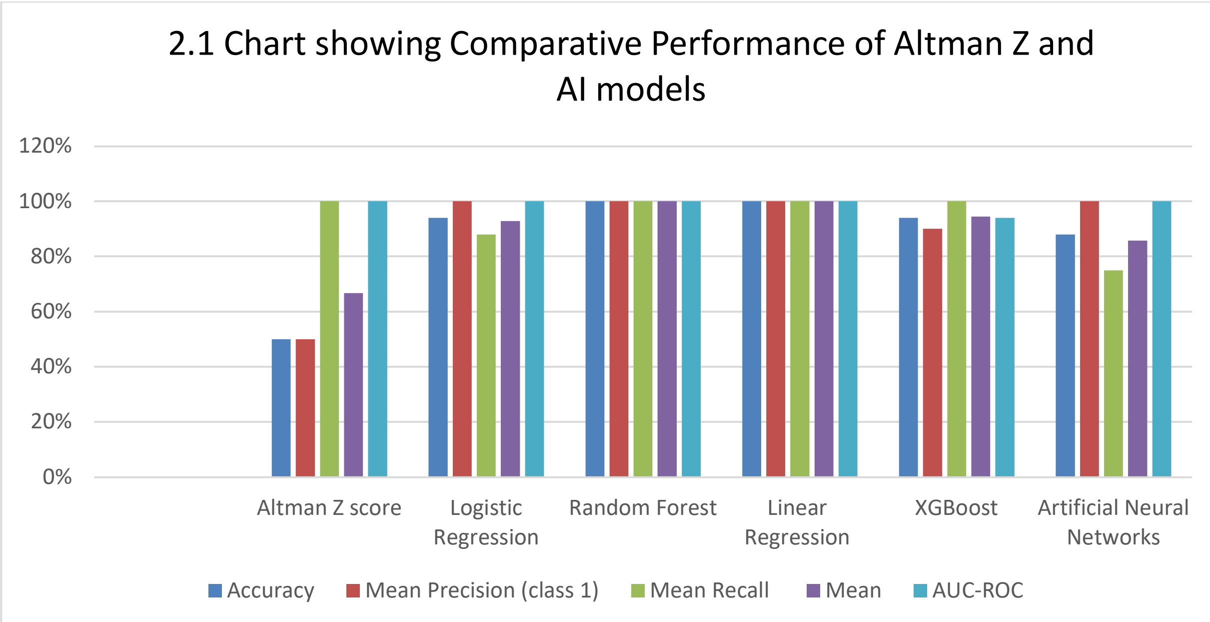

Interpretation:

With 50 percentage, Altman Z reports moderate and low predictive accuracy. The mean precision of 0.50 shows that 50 percent of the classifications are right which is judged as moderate to dependable. Mean Recall Mean Recall shows that the mode is 0 false negatives. The mean F1=0.6666 indicates the mediocre performance of the model and improvement is required.

The Logistic Regression Model is very precise that it has a Precision of 1.00 with 94% Accuracy and shows zero false positives which is the highest value of precision. The excellent recall of 0.88 is a sign of a high-performing model and the Mean F1 score of 0.9285 is also excellent, which balances the precision and recall.

Random Forest Model is regarded as an ideal predictive model and one that has a hundred percent accuracy, no false positives, mean precision = 1.00 and a Mean Recall = 1 i.e. the model has no false negatives and it detects all the positives in the dataset which is a perfect score. A mean F1 score of 1.00 is a balance between precision and recall and is to signify that the model is a perfect predictor.

Point wise, The Linear Regression Model equates with the random forest, is very accurate with no false negatives, and at the same time has a zero false negative, which is a perfect balance of precision and recall, thus regarded as an accurate and reliable model, yet, it can only work with linear and straightforward data, making it less desirable than random forest.

XGBoost has accuracy of 94, it is said to be an accurate and closed prediction model as compared to monitoring forests, and the mean precision value is 0.9 which means that there are only a limited number of false positives; Mean Recall1 has a value of zero and F1 Score is 0.9444 which is interpreted to show that there are only few false positives and a strong balanced precision and recall.

The ANN model was quite accurate and lower than the other AI models, the average of precisions is 1 (no false positives), the average recall is 0.75 (some false negatives), and the average F1 score is lower than the Top Predictors or Feature Importance in the above AI models. It is believed that the random Forest model is the most accurate model in predicting financial distress and the importance of the features is illustrated individually.

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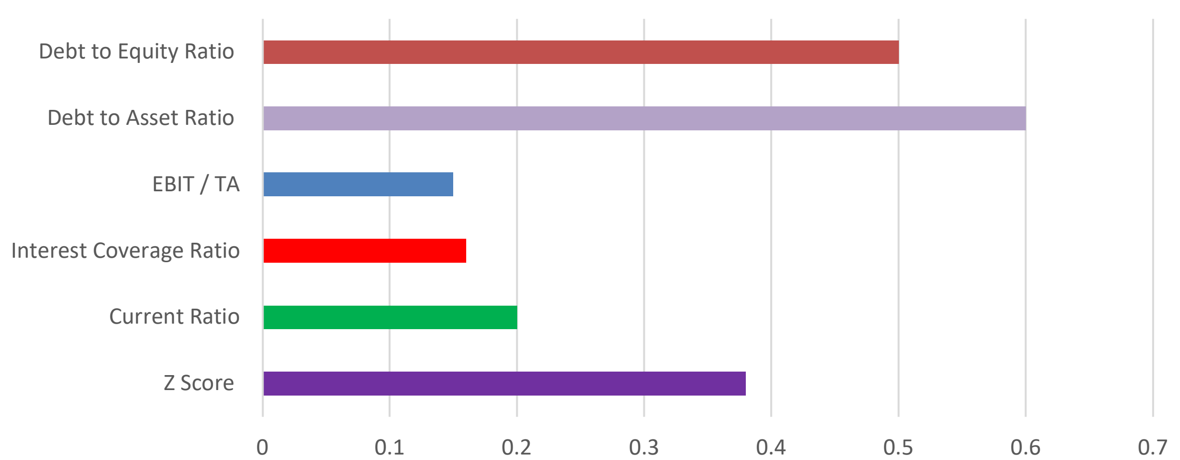
2.2 Table showing Feature importance of Random Forest Model

Feature	Z Score	Current Ratio	Interest Coverage Ratio	EBIT / TA	Debt to Asset Ratio	Debt to Equity Ratio
Importance	0.38	0.20	0.16	0.15	0.6	0.5

2.2 Chart Showing Feature Importance used in Random Forest Model



Interpretation: The above graph shows that Debt to Asset Ratio is the most important feature in the Random Forest model, followed by Debt to Asset Ratio and Altman Z-score. EBIT/TA has the least feature importance in the Random Forest model.

2.2 Table showing Feature Importance used in Logistic Regression, Linear Regression models, XGBoost models

Feature Importance	Logistic Regression	Linear Regression	XGBoost
Z Score	0.019729	0.543158	1.00
ICR	0.053768	0.452632	0.0
EBIT/TA	0.01644	0.164986	0.0
Debt/Equity Ratio	0.5194	0.000035	0.0

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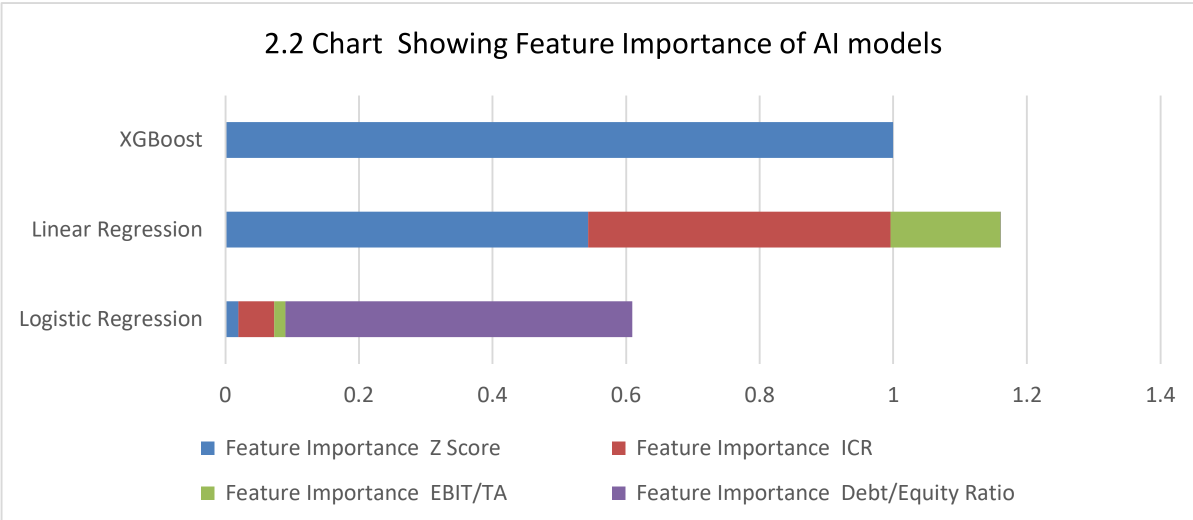

(Source: Compiled by the author)

As the graph shows, the Altman Z-Score has the highest level of feature importance, based on the XGBoost model. The Altman Z-Score is also the most significant in the Linear Regression model with interest coverage ratio (ICR) and EBIT/Total Assets (EBIT/TA) in the second and third positions respectively and the Debt-Equity Ratio is the least influential factor. The Logistic Regression model, on the other hand, shows the Debt-Equity Ratio to be the most important predictor with the lowest degree of importance belonging to the EBIT/TA.

Analysis of the significance of financial leverage ratios on Financial Distress: Regression-based evidence

2.3 Table showing the relationship between the Financial Distress and leverage ratios.

Ratios	Coefficients	Standard Error	P – Value	Interpretation
Debt to Equity	-11.47221589	4.204198796	0.0172	Inversely significant
WC/TA	50.53688482	18.47515137	0.017005625	Positively significant
EBIT/TA	21.25395248	16.52414537	0.220797067	Insignificant

(Source – Data processed through Excel)

Table 2.3 reveals that the '*Debt-to- Equity ratio'* has a negative coefficient whose p-value is 0.0172, which implies that there is a strong negative relationship between them i.e. an increase in the value of debt as compared to equity would reduce the chances of financial distress. The coefficient of the '*Working Capital to Total Assets (WC/TA)'* ratio is positive and the p-value stands at 0.017, which implies that the working capital to total assets has a very strong positive relationship and, in this case, the higher the working capital of a firm in relation to its total assets, the healthier the business. Conversely, the p-value of EBIT to Total Assets (0.220) is not below 0.05; this implies that the two variables do not have any statistically significant relationship with the financial distress.

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Findings of Hypothesis Testing

The model of Altman Z-score obtained a predictive accuracy of 50 percent, compared to AI-based models that provide a 100 percent predictive accuracy of Random Forest and Linear Regression. It means that the predictive-performance of the traditional Altman's Z-score and AI-based method differs significantly. In turn, the null hypothesis (H01) is void and rejected, and the alternative hypothesis (H11) is accepted. Therefore, the null hypothesis (H0 2) is not accepted since there is a correlation between the financial leverage ratios (Debt to Equity and WC/TA) and probability of financial distress among the Indian manufacturing companies.

Conclusion

In a nutshell, the analysis of the Altman Z-score indicates that all the chosen manufacturing companies were not in a financially struggling condition. Nonetheless, the use of AI-based predictive models was more accurate and time-sensitive as compared to the classical Altman Z model. The model that was the most useful in the case of predicting financial distress was the Random Forest algorithm. In addition, the results indicate that there is a strong important relationship between Debt-to-Equity ratio and Working Capital-to-Total Assets ratio, and the likelihood of financial distress amongst manufacturing companies.

Limitations and Future research directions:

By pointing out the shortcomings of the current research, future researchers are expected to overcome them and come up with an improved research.

a) To maximize the accuracy of the research outcome, it is possible to increase the sample size of both financially distressed and not financially distressed.
b) One of the things that can be considered is to conduct a study by increasing the number of financial years.
c) Then, the research can be extended with algorithms of machine learning like *K-Nearest Neighbours,* Support Vector machines, and Naive Bayes as well as a discussion of the feature importance in the ANN model.

References

(1) Jyoti Nair and J K Sachdeva (2022) Predictive Modelling for Financial Distress amongst Manufacturing Companies in India, Journal of Global Economy, Volume 18, No 4, December 2022.
(2) Igal Hendal (1996) Competition under Financial Distress, The Journal of Industrial Economics, Volume XLIV, 0022-1821, September 1996.
(3) Vincent & Dakare (2019) Financial Distress Overview, Determinants, and Sustainable Remedial Measures: Financial Distress, Corporate Governance Models and Applications in Developing Economies, September 2019.
(4) Arhinful & Radmehr (2023). The Impact of Financial Leverage on the Financial Performance of the Firms Listed on the Tokyo Stock Exchange, Journal of Capital Market Studies, June 2023.
(5) Xiuxia Li (2025) Research on the Impact of Financial Leverage on Corporate Capital Structure, Journal of Modern Business and Economics, February 2025
(6) Lokanan & Sana Ramzan (2024) Predicting financial distress in TSX-listed firms using machine learning algorithms, Frontiers in Artificial Intelligence, November 2024.
(7) Nandita Mishra, Shruti Ashok, and Deepak Tandon (2021), Predicting Financial Distress in the Indian Banking Sector: A Comparative Study Between the Logistic Regression, LDA, and ANN Models, Global Business Review.
(8) Sehgal, Mishra, Diesting, and Vashisht (2021). On the Determinants and Prediction of Corporate Financial Distress in India, Managerial Finance Manuscript ID MF-06-2020-0332.R3.
(9) Shrivastava, Nitin Kumar, Kuldeep Kumar, Sanjeev Gupta (2020), Corporate distress prediction using random forest and tree net for India, Journal of Management and Science.

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(10) Andrade and Kaplan (1998), How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed, National Bureau of Economic Research, Working Paper 6145 http://www.nber.org/papers/w6 145
(11) Annual Reports of Tata Steel from the annual year 2021-22 to 2024-25
(12) Annual Reports of Ashok Layland for the annual year 2021-22 to 2024-25
(13) Annual Reports of HUL for the annual year 2021-22 to 2024-25
(14) Annual Reports of JSW Steel for the Annual year 2021-22 to 2024-25